THE NUANCED ROLE OF SOCIAL RELATIONSHIPS IN SUB-SAHARAN VILLAGE ECONOMIES

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This dissertation explores the nuanced ways in which heterogeneity in social relationships and community characteristics influence processes of economic development. It contributes novel theoretical and empirical insights using a combination of social network analysis on originally collected surveys of farmers in Ghana and Malawi. Each chapter highlights the nuanced and unique contributions of social networks within village economies, including the ways they influence decision-making through social learning processes and local norms of redistribution. Chapters two and three suggest that variation in bonds of friendship influence the quality of information one receives and the extent to which redistributive giving leads to efficient outcomes. Chapter four explores a common policy framework utilized by governments and NGOs to engage with communities as comprehensive units of society. It finds that variation in capacity for local collective action is not adequately harnessed when NGOs and governments deal with communities in a homogeneous manner. As a whole, this dissertation invites a new path of inquiry that takes seriously the varying degrees to which communities possess the capacity to influence economic development. The nuanced understandings of community economies invites future research to consider means of integrating community functions into development policies that have historically depended on broadening access to mutually beneficial exchange through markets.

BIOGRAPHICAL SKETCH

Vesall Nourani was born in Wisconsin in June of 1986. At the age of ten, he moved with his family to Bratislava, Slovakia for six formative years. In 2002, he moved back to the United States of America, graduated from Chapel Hill High School in North Carolina in 2004 and the University of North Carolina at Chapel Hill in 2008. During this period, prior to his PhD training, he resolved to serve his local community through the grassroots activities of the Bahá'í community in lieu of pursuing work and study opportunities in other locales. This experience deepened his appreciation of social relationships in local communities, which drove him to aspire to deepen his understanding of community phenomena through research. He married his wife, Sally Whisler Nourani, in 2008 and in 2012 they moved to Ithaca, NY to pursue graduate degrees at Cornell University. While in Ithaca, they welcomed two wonderful sons into their family, Faizi Nourani in 2013 and Monib Nourani in 2016.

This dissertation is dedicated to my contemporary young Bahaí'ís in Iran, who risk their freedoms each day by enrolling in institutions of higher education.

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It is a gross understatement to state that I owe every one of my achievements to the Blessed Beauty, Bahá'u'lláh, whose divine revelation is the source of any of my thoughts that can be characterized as inspired. I hope my efforts at uncovering aspects of social reality through my research does justice to the generative power of His Word. My wife, Sally, has been a constant source of wisdom and clarity during the most trying times — all while being a model academic in her perseverance in pursuing a Master's degree during our time at Cornell. I have been the beneficiary of intellectual support through my brother, Sana, and the immense power of his intellect. Indeed, many of my academic decisions can likely be traced back to conversations we have shared. My children, Faizi and Monib, have filled my heart with love and reminded me to seek joy in the simple experiences of life. I am indebted to them for providing measured perspective on the importance of living a balanced life during the intensity of a PhD training. My mother, Fahimeh, father, Vahid, and sister, Parisa, have perhaps had more faith in me than I ever had in myself — their encouragement fueled much of this journey. The practical support of both my parents and parents-in-law, John and Carolyn, can not be understated and are also worth more than my printed dissertation's weight in gold. Similarly, it is highly unlikely that this PhD would have been completed without the support of my local Ithaca community and Alba Sancho in particular. The loving support and assistance she showered on our family when we were learning to manage life with infants allowed me to maintain connections to my intellectual pursuits without compromising family commitments. I am intellectually indebted to my supportive committee members: Chris Barrett, Larry Blume and Eleonora Pattachini. The mentorship provided by them, Holly Hanson and the Institute for Studies in Global Prosperity gave me the confidence to persevere in infusing my research with the creative inclinations of my intuition. Numerous others deserve my gratitude and I deeply regret not having the space or memory to grant them adequate acknowledgement.

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CHAPTER 1
INTRODUCTION

The English monetary economist Dennis Robertson once suggested... that using the market to accomplish the basic tasks of life frees up energy for other ways of connecting. "What does the economist economize?" Sir Dennis asked rhetorically... His answer: "That scarce resource Love, which we know, just as well as anybody else, to be the most precious thing in the world." By using the impersonal relationships of markets to do the work of fulfilling our material needs, we economize on our higher faculties of affection, reciprocity, personal obligation — love, in Robertsonian shorthand — which can then be devoted to higher ends.

— Marglin [2008], *The Dismal Science: How Thinking Like an Economist Undermines Community*

The process of modern economic development has been intimately tied to the twin social phenomena of capitalism, characterized in it's crudest form by private property rights, and industrialization. As with any process that shakes the foundation of human society, it has been accompanied by a consistent question — are social connections compromised as modern institutions enable the proliferation of anonymous transactions through modern (state-enabled) market mechanisms? Polanyi [1944] flagged this as a major concern of the "Great Transformation" that accompanied industrialization. Among his arguments was that the commodification of labor, land and money disconnected people from the communities they belonged to during the era of industrial transformation in Britain, replacing social forms of insurance and care with a rule-based system that treated humans as inputs in a broader social machinery. In a similar vein, Scott [1998] argues that the state's approach of standardizing its relationship with its constituents has resulted in unintended social ills throughout history, of which the decay of social orders founded on relational interactions is a part.

The common counterpoint to these (admittedly simplified) criticisms of industrial capitalism is that it is easy to romanticize social systems of the past, thereby neglecting to acknowledge the gross injustices committed to individual freedoms. Indeed, a broad strand of research in modern development economics has studied the ways in which extant social norms and practices in developing, predominantly agrarian, societies affect the normative ends of economic efficiency [Platteau, 1994a,b]. Additionally, it has been argued that access to broader markets has the potential to introduce goods and services that increase connections among people, in other words they serve as complements to social networks [Gagnon and Goyal, 2017]. Under the right conditions, economic development may serve to strengthen social connections within a population.

I do not claim that the present dissertation answers the age-old question "are markets good for social relationships?" Neither do I intend to make progress in answering this question in particular. Rather, I take the stand that it is more valuable to begin an enquiry by addressing the significant heterogeneity in the capacity of communities to generate welfare-enhancing outcomes. Instead of giving in to the dichotomy of deciding which side of the normative binary community economies stand on, the aim of this dissertation is to look *within* communities in order to enhance our understanding of the properties that might make social forms, as opposed to modern market-forms, of economic organization laudable in the first place. A natural starting point is to think deeply about the quality of social relationships within communities and how they influence well-known economic phenomena that rely on sociality.

Summary of Dissertation Research

The questions under consideration are the following: "how does information provided by close friends influence investment decisions relative to information we glean from acquaintances"; "under what conditions are gifts to other households determined by love as opposed to the force of social pressure", and "how does a uniform approach to community engagement hinder community driven development programs?" It is hopefully evident to the reader that the flavor of these questions is more consistent with "under what conditions do communities enhance economic well-being" than "whether communities enhance economic well-being."

To this end, I focus my analysis in sub-Saharan Africa, a region of the world in which, in its most general sense, social relationships play an outsized role in determining economic well-being relative to other regions. I do this by analyzing the nuanced and unique contributions of social networks within village economies to processes of economic development, including the ways they influence decision-making through social learning processes, local norms of redistribution, and decision-making rules used by village civic organizations. I outline each of the three chapters which tackle these questions below.

Although it is well-established that social learning plays a role in farmers' decisions to adopt new agricultural technologies, less is known about the social influence of disadopters—peers who discontinue use of a new technology. Chapter 2 shows is the first study to show the distinct social influences of disadopters. The core insight is that the influence of a disadopter depends on the proximity of his or her social tie with a potential adopter of a new technology. I develop a new model of social learning along networks that separates farmers' beliefs of the average profitability of a new crop from their knowledge of how to produce it. To learn how to produce the new crop, farmers pay a learning cost, and once acquired, production knowledge increases the expected profitability of the crop. Learning cost is a decreasing function of peer experience and social proximity. It is more likely that socially proximate farmers of the new crop help peers acquire production knowledge, but socially distant peers influence profitability beliefs from their observable (adoption and disadoption) decisions. I test these implications using a hazard model and a novel data set of pineapple farmers in Ghana, and find consistency with the model. Disadoption by socially distant peers is more likely to decrease adoption probability than similar disadoption by socially proximate ties, and adoption by socially proximate peers increases adoption probability. This latter effect does not exist when farmers have low profitability beliefs, proxied by an exogenous negative shock to pineapple prices. Interpreted through the lens of the model, results suggest that socially distant and proximate peers contribute to distinct types of learning processes—distant peers influence profitability beliefs, and proximate peers also facilitate production learning.

In chapter 3 we model limited commitment informal insurance networks among altruistic individuals where the impurely altruistic gains to giving to others diminish with the number of transfers one makes; giving is costly, and stochastic income has both publicly observable and unobservable components.[1] Contrary to the canonical informal insurance model, in which bigger networks and observable income are preferable, This model predicts that unobservable income shocks may facilitate altruistic giving that better targets the least well off within one's network and that too large a network can overwhelm even an altruistic agent to cease giving. We take these predictions to a unique data set from southern Ghana. We couple observations of gift-giving networks with experimental cash windfall gains - randomized between private and publicly observable payouts - repeated every other month for a year to analyze transfer flows among households. We find four striking results. First, on average, more gifts are given out of private cash winnings than public cash winnings, signaling that

[1] Chapter 3 is written in collaboration with Chris Barrett, Eleonora Pattachini and Thomas Walker.

altruistic preferences - not just self-interested behavior within an endogenously enforceable insurance scheme - must be a significant driver of inter-household transfers. Second, winners of privately revealed prizes target giving to the neediest households within their networks, indicating greater social welfare gains from altruistic transfers than from insurance transfers. Third, winners of publicly revealed cash prizes do not make transfers when they have large networks; they break the informal contract due to network size. Fourth, conditional on transfers flowing within one's network, we cannot reject the null of full risk pooling. These results highlight the limits to social networks as channels for managing income shocks as well as the trade-offs inherent to transparency in transfer programs. Although observability of income is essential in informal insurance arrangements among purely self-interested agents, observability may impede altruistic agents' ability to focus their giving on the most needy as they are compelled to respond to demands for assistance from the less needy within their network.

Chapter 4 uses the results of a public goods game with farmer clubs in Malawi to determine the socio-political conditions that increase cooperation.[2] We find that democratically-run clubs contribute more than clubs with leader driven decision-making. Focus groups indicate that democratic clubs use deliberative discussion and that this form of decision-making is generally selected to mimic norms of decision making commonly present within the village. We show that decision-making processes in "other" civic organizations within the village are highly predictive of our farmer clubs' decision-making rules, suggesting norms of cooperation that exist at the village-level. The norm is shown to be persistent in two ways. First, there is no effect on contributions to public goods when we experimentally change decision-making rule within villages. Second, contributions only increase in democratically-run clubs when relationships are characterized by close social connections among club members. Then, we

[2]Chapter 4 is written in collaboration with Annemie Maertens and Hope Michelson

show that, likely due to ease of facilitating activities with farmer clubs whose leaders have more power over decision-making, a partnering NGO seeking to benefit from the capacity for collective action at the local level focuses its interactions on clubs with more vertical power structures. Along ever measure available to us, such authoritarian clubs interact with the NGO to greater extents than clubs with democratic power structures despite the fact that the reverse pattern is seen in our measures of club-level collective action. This suggests that the homogeneous treatment of communities by protagonists of community driven development programs leads to preferential interactions with the types of communities who fit the NGO's model of interaction — in our context, these communities were less capable of the capacity for collective action coveted by the NGO.

There is a core insight that weaves the conclusions of the three studies in this dissertation into a single fabric: stronger relationships among members of a community lead to locally desirable economic outcomes. In the context of technology adoption, socially proximate ties enable farmers to learn production methods which has the effect of minimizing production errors, thereby increasing expected profits. In this context, socially distant friends may influence farmers to make errors of judgement if information signals generated by disadopters, for example, incorrectly guide a population into an information cascade with inefficient outcomes. In the context of voluntary redistribution through gift-networks, certain conditions on the observability of income enable households to altruistically target resources to households who serve to benefit the most. Thus, informal transactions among households motivated by altruism may lead to more efficient distributional outcomes. Finally, in our analysis of the determinants of contributions in public goods games in farmers clubs we find a high degree of heterogeneity in community capacity for collective action. A worry is that policy-makers are blind to this heterogeneity and perceive communities to be receptive to a new program only if they cohere with the types of behaviors expected of them in their relations with the

NGO. Unfortunately, in our setting, the particular type of relationship between NGOs and the communities they interact with strengthen clubs with lower capacity for collective action.

A Path Forward

On its surface these insights are somewhat intuitive, though the systematic documentation of the nuanced ways in which different types of social relationships and communities influence economic well-being is a unique and important contribution of this dissertation. In making this contribution, this dissertation deepens understanding of the various ways in which social relationships *within communities* influence important economic outcomes, thereby demonstrating that it behoves both the scholar and the policy maker to approach communities as more than a "black box" in research or policy-making that consider "social capital" as an exogenous variable. A more nuanced approach in which the heterogeneous nature of social relationships within and across communities is documented and leveraged when appropriate may be more effective in uncovering truths about social reality and designing policy in a practical manner to improve human well-being.[3] Furthermore, the theoretic contributions of this dissertation allows more general insights into approaches to economic development that consciously magnify Marglin's [2008] desired qualities of "affection, reciprocity, personal obligation — love."

Thus, it is worthwhile to outline how this dissertation highlights a promising path for future research. Chapter 2 shows that relationships characterized by strong ties facilitate a more scientific approach to learning novel agricultural production methods — strong ties can more easily question one another about the relationship between inputs and outputs, which leads to refinement of production models over time. Rather than introducing new

[3] Indeed, it is not implausible to conceive of policies that may be designed in ways that incentivize relationship-building within communities.

agricultural technologies to communities based on a belief (from outside the community) that the technology is beneficial, would not a more preferred outcome be to enhance the process by which community members can objectively distinguish good versus bad investment opportunities? If social networks implicitly rely on scientific methods (i.e., by combining observation with model refinement) to determine such opportunities, would it not be beneficial to make such methods explicit through training in the scientific method? Given the increasing prevalence of governments and NGOs direct engagement with communities, such an approach does not seem far from practical. Indeed, it may also enable more communities with decentralized power structures, those communities with higher capacity for collective action in chapter 4, to enhance their deliberation processes in a way that utilizes and contributes to interactions with NGOs and governments — protagonists of community driven development models.

In chapter 3 we introduce a model that combines altruism, risk-aversion and network size to form testable hypotheses. A next step could be to structurally estimate parameters associated with altruism, network structure and risk aversion from the data. This enables an assessment of the relative welfare implications of public versus private giving, both under the conditions in the tested villages and under different conditions — for example, as capacity for altruistic behavior changes. In essence, we could ask under what conditions are social enforcement mechanisms necessary to achieve socially beneficial levels of sharing? Under what conditions are they counterproductive?

Such questions also invite researchers to consider the relationships between altruism, network structure, and the enforcement of kinship taxes. Do villages with characteristics that predict the failure of voluntary giving networks have stronger social enforcement mechanisms than those with characteristics that predict the success of voluntary giving networks? Do kinship taxes and similar norms appear when theyâĂŹre most adaptive? What happens to social enforcement when an intervention increases altruism or enriches social connections in a community? For example, do social enforcement norms weaken when intrinsic motivations drive giving?

The discussion in the above two paragraphs also suggest a broader concern of dealing with "community economies" that is, perhaps, more philosophical in its scope — that moral concerns cannot be side-stepped in community settings since self-interested explanations of behavior prove inadequate. Indeed, a thorough understandings of the degree of social processes in an economy requires analyses of the types of localized relational interactions that are themselves dependent on moral values developed in processes of socialization. It seems important, then, to consider spaces where socialization occurs, the degree of shared understanding of moral responsibilities towards groups in these settings, and the coherence between the specific moral values magnified in these spaces and the desired end of economic prosperity.

To this extent, it seems valuable to embark on an analysis of schooling in economies in which social relationships play an important role in determining economic well-being.[4] Among the questions worth asking are: what types of relationships are cultivated in schools among students, between students and teachers, teachers and administrators and between teachers, administrators and parents? Do the values generating these relationships cohere with the positive values of reciprocity, trust, and other-regard that prove useful in economic exchanges based on social interactions? Can different approaches to schooling attenuate

[4]The discussion in Bowles and Gintis [1977] provides a valuable starting point in this regard. Bowles and Gintis [1977] posit that progressive attempts at schooling reform in America in the 1960's were hindered by the lack of coherence between the ideals of egalitarianism in education systems and the innate hierarchies present in modern capitalist economies. Relationships between managers and employees, capital owners and laborers, etc. are dependent on the types of distant relationships present between teachers and students, administrators and teachers, teachers and parents, etc. For example, the freedom to "hire" and "fire" that is central to the behavior of American firms is cultivated in the approaches to student assessment in American schools.

harmful traditions present in some approaches to community life?[5] To what extent is local knowledge integrated into school curricula? Do the skills, attitudes and knowledge developed in schools balance the needs and concerns of their surrounding communities with those of national economies? Given that many parents in developing countries perceive a trade-off between contemporary modes of schooling and participation in local labor force, it is worthwhile to pursue a research agenda that explores whether an approach to schooling that achieves greater coherence between the two can also increase learning quality, school enrolment, years of schooling and economic productivity.

Finally, while it is clear that stronger relationships within communities lead to improved *local* economic outcomes, it is often the case that these relationships come at the expense of greater levels of economic prosperity derived from generalized trust (i.e., robust market economies and the legitimate power of their necessary laws and institutions). This suggests that a research program considering the role of local communities in processes of economic development would benefit from exploring qualities of community economies in which the benefits of generalized trust do not exist in opposition to high quality, local, social relationships. What types of identities (and accompanying moral values) can be cultivated that generate these ends? Is it possible to overcome the definitionally limited identities formed by kinship, ethnic, caste-based, ideology-based, village or tribal networks without compromising the immense capacity for collective action, information sharing, and other-regard that exists within such groups? These, and other similar questions, will be difficult to address without a more interdisciplinary approach to inquiry than the type of inquiry presented in this dissertation.

[5]For example, the tendency to cooperate with an "in-group" at the expense of interactions with an "out-group" as in Rao [forthcoming].

CHAPTER 2

MULTI-OBJECT SOCIAL LEARNING AND TECHNOLOGY ADOPTION IN GHANA: DISTINGUISHING BELIEFS FROM KNOWLEDGE

2.1 Introduction

Modern agricultural technologies have increased productivity for countless farmers worldwide, yet various barriers have prevented widespread adoption in sub-Saharan Africa [World Bank, 2007, Jack, 2011].[1] One barrier is lack of information regarding the applicability of new technology to one's own fields. When outside sources of information are scarce, farmers turn to social networks to learn whether or how to farm a new crop [Foster and Rosenzweig, 1995, Munshi, 2004, Bandiera and Rasul, 2006, Conley and Udry, 2010a].

The primary narrative is that new technologies are uniformly and unambiguously superior to traditional forms of production, but the reason they remain unadopted, however, is that farmers lack knowledge on how to use technologies in practice. Farmers can learn production techniques from experienced peers in their social networks, and this learning increases expected profits and leads to increased rates of adoption (or profits). This narrative neglects a second line of evidence that suggests that adopters often realise lower-than-expected returns to technologies [Duflo et al., 2008, Marenya and Barrett, 2009, Suri, 2011, Magnan et al., 2015], which leads to discontinued use, or disadoption, during a subsequent period [Moser and Barrett, 2006, Zeitlin, 2011].[2]

How does disadoption along a social network influence processes of social learning? A

[1] For an overview of the literature on factors that influence technology adoption, see Feder et al. [1985], Barrett [2005], Foster and Rosenzweig [2010].

[2] The quality of new technologies available for purchase vary [Bold et al., 2017], and international price changes make seemingly profitable technologies unprofitable later [Ashraf et al., 2009, Maertens and Swinnen, 2009, Harou et al., 2017]. These phenomena also lead to disadoption.

disadopting peer might induce one to believe that a new technology is not worth one's time, and consequently, peer experiences help answer the question of whether to adopt a new technology. However, any farmer with experience using a new technology, as a current or former user, can help peers learn how to use the technology. It is reasonable, then, to distinguish objects of learning along these lines.[3]

I construct a model that distinguishes two pathways of social learning—learning that leads to 1) production knowledge (e.g., skills, production practices, and know-how) and 2) beliefs about the profitability of a new technology.[4] I test the model's implications in an empirical context of Ghanaian pineapple farmers using a dataset with detailed information of within-village social networks, and the year of each individual's adoption and disadoption behaviours during a period when pineapples were introduced (early 1990s through 2000s). Results are consistent with the model implications. Peer disadoption delays diffusion of a profitable crop. By understanding how disadopters influence peers, policies that leverage social learning can be rethought.

The two pathways of learning described above can be thought of as occurring over successive stages and periods. Since returns to new technologies are heterogeneous (i.e., due to either farm or farmer characteristics), each farmer in a population draws beliefs from a probability distribution in an initial period, and updates these beliefs in a DeGroot fashion along a network. This implies that farmers take a weighted average of their peers' beliefs during period $t-1$ into each subsequent period t.[5] If farmers decide to adopt the new crop, their

[3]Objects of learning are delineated similarly by Oster and Thornton [2012], who corroborate that peers are more effective at showing friends how to use menstrual cups and less effective at influencing whether to use them.

[4]This approach is similar to Fafchamps et al. [2016] and Banerjee et al. [2016]. The former models learning as distinguishing between learning about the existence of a product and learning the hidden qualities of a new product through use. The latter models information diffusion that occurs simultaneously with information aggregation; when information is not diffused, it is also not aggregated (i.e., the source of unknown unknowns).

[5]I choose social learning heuristics for each object of learning to match their empirical qualities. Specif-

profitability beliefs depart from DeGroot updating and they asymptotically learn their true profitability over time. This last component allows disadoption when farmers overestimate profitability prior to adoption. DeGroot learning implies that one farmer's decreasing profitability beliefs can decrease others' beliefs over time. A non-adopter's profitability beliefs can decrease while peers consider disadoption.

Relative to profitability beliefs, production knowledge is cognitively challenging to acquire.[6] There is a trade-off between the benefits to expected profitability that accrue when knowledge is acquired and the costs of acquiring it. Social learning allows learning costs to be a decreasing function of peer experience using the new crop. If and only if profitability beliefs are above a lower-bound threshold for a farmer, he/she might choose to acquire production knowledge. Production knowledge refines a farmer's ability to produce a new crop in practice, which strictly increases profits in expectation.

The insight in this part of the model is that when learning costs are too large relative to profitability beliefs, farmers might be rationally inattentive to information that refines their ability to use a new technology.[7]

The relationship between profitability beliefs and cost of acquiring production knowledge provide an interpretive lens to any binary choice model in which a lumpy learning investment is required to refine one's ability to act. For example, beliefs about the benefits

ically, I model profitability beliefs using a modified DeGroot updating procedure. As Chandrasekhar et al. [2015] argue, unlike Bayesian learning, DeGroot updating need not require that populations of agents converge to the same belief. In practice, this means that DeGroot learning might lead some agents to find a new crop profitable while others do not. This is an attractive quality for agricultural applications, given heterogeneous returns to new technologies in most real-world contexts.

[6] Production knowledge is tied to a target input model; farmers are penalised when an input application does not match the required level of input (e.g., fertiliser). Production knowledge increases the chances of correct input application.

[7] This approach is similar to that suggested by Caplin et al. [2015], in which agents learn from others how attentive they should be to certain categories of information. Rational inattention was first studied by Geanakoplos and Milgrom [1991] and made popular by Sims [2003]. Ghosh [2017] similarly models a learning cost in a model of rational inattention that decreases with peer experience.

of selecting into an occupation do not alone determine occupation choice; agents naturally weigh the benefits against the costs required to learn occupation-specific tasks. Similarly, educators are informed about teaching practices that enhance student learning, but might not know how to apply these practices to their circumstances without additional learning. Attempts at inducing selection by increasing agents' beliefs alone might not achieve desired outcomes. High learning costs prevent selection of a potentially beneficial choice, even if the new alternative is believed profitable.

Required of an empirical context is adoption of a new technology or crop, followed by disadoption in at least a subset of cases. The setting should be one in which farmers acquire production knowledge from peers. Thus, I analyse model implications in an empirical setting in which the latter is known to be true—one in which farmers in three Ghanaian communities acquire production knowledge on pineapple cultivation techniques by analysing the experiences of peers [Conley and Udry, 2010a].[8] I use data that extend the panel used by Conley and Udry [2010a] (collected in 1997–1998) to 2009, which additionally asks pineapple farmers to recall the month and year during which they disadopted pineapple. Thus, I use information on the timing of pineapple adoption and disadoption in each of the communities, and combine this information with rich social network data, to test model implications using a hazard model to study the role of social influence on selection into pineapple cultivation. Crucially, many farmers disadopted pineapple after initial experimentation throughout diffusion, as shown in figure 2.1.[9]

[8] Conley and Udry [2010a] show that farmers seek to enhance their knowledge of optimal fertiliser use during production of pineapple. Farmers move their own input configuration toward inputs used by peers when peers have high expected profits 12 months after applying a particular amount of fertiliser. Conversely, they do not shift toward the input use of peers who experience low expected profits.

[9] Figure 2.1 shows that villages with higher relative rates of disadoption during early stages of diffusion were much slower to adopt pineapple later. One of the four villages was excluded in Conley and Udry [2010a] because of the nonexistence of pineapple farmers in the 1996–1998 sample. Figure 2.1 shows that the village Konkonuru had the earliest incidences of pineapple disadoption, which might have swayed others from adopting.

I generate nuanced model implications by combining social network data features with assumptions regarding the role of social proximity in determining information flows among village residents. I assume that all actions (i.e., nonadoption, adoption, and disadoption) along a network are observable, but that communication among strong ties (ST) is more likely than communication among weak ties (WT).[10] I further separate risk-sharing ties in measurement of STs and WTs due to their confounding influence on adoption through learning. The data show that family members participate in resource-pooling with one another (as in den Broeck and Dercon [2011] and Angelucci et al.). Even if information communicated among family members is akin to ST communication, the possibility of risk-sharing might induce strategic substitutability—a farmer might be less likely to increase the family's risk burden by adopting a risky crop—which negates possible social learning effects.[11]

The ensuing model implications can be placed in two categories—how changes to profitability beliefs influence adoption, and how changes to learning costs influence adoption. In the former category, I expect positive (negative) correlations between the network share of adopters (disadopters) during period $t-1$, and adoption probability during period t. Since farmers act as though WT actions represent an intertemporal aggregation of beliefs when their actions occur, WT effects are predicted to be larger in magnitude than ST effects. In the latter category, changes to learning costs influence adoption only if profitability beliefs are sufficiently high. Thus, the sum of experienced peers during period t influences adoption probability positively only if profitability beliefs are sufficiently high. ST effects

[10] This is what Granovetter [1973] suggest. Communication costs are similarly modelled in Niehaus [2011]. The data allow me to categorise "close" or "good" friends as STs, and "distant friends" or "acquaintances" as WTs. Granovetter [1973] suggest a similar categorization.

[11] Network actions serve as strategic complements or substitutes; in addition to spreading information, network externalities change other incentives for adoption of a new technology, inducing or delaying adoption by peers.Granovetter [1978] was first to model the role of strategic complements during diffusion. For an overview, see Jackson and Yariv [2011]. For a discussion of conditions under which network actions are complements or substitutes, see Galeotti et al. [2010].

are predicted to be larger than WT effects due to the ease of communicating the results of cultivation practices.

I estimate a discrete-time hazard model with time-variation in peer adoption and disadoption behaviours to link estimated coefficients to each of eight testable model implications.[12] I find consistent support for the model of multi-object social learning. The effect of WT disadoption on own adoption is large and economically significant; when the share of WT disadopters increases by 20 percentage points (from zero), I observe a 60 percent decrease in the probability of adoption (figure 2.2). Each experienced ST increases the probability of adoption by 6 percentage points, conditional on beliefs that suggest that the new technology is profitable (figure 2.3).[13] Family adoption and disadoption behaviours decrease the probability of adoption, suggestive of the fact that families hedge against each others' adoption behaviours (of a risky crop).

Estimating the influence of peer behaviours is difficult since unobservable individual characteristics often correlate with unobservable peer characteristics, generating spurious correlations. I argue that this is less of a concern during my analyses because of nuanced implications generated by distinguishing WT from ST, and profitability beliefs from production knowledge. First, and as predicted, WT effects are stronger than ST effects when testing model implications tied to profitability beliefs. Spurious correlations cannot drive these results if STs are more similar to one another than WTs are, as is often presumed. Second, I show that STs do not influence adoption probability when there are reasons to

[12] Hazard models are a type of time-to-event analysis, in which one analyses the amount of time between potential exposure to an event and occurrence of the event. The event is adoption of pineapple. The discrete nature of the time variable allows me to incorporate time fixed-effects; I do not assume a parametric effect for the time trend. For a discussion of hazard model analysis, see Allison [1982]. For an example of a study that analyses social learning effects using a hazard model of technology adoption, see Genius et al. [2014].

[13] The effect of peer disadoption has not been tested in the literature. The effect of ST adoption on own adoption is similar to the marginal effect evaluated at the mean, 5.4 percent more likely to adopt, in Bandiera and Rasul [2006].

believe that farmers hold low profitability beliefs. ST effects are only positive 1) prior to a pineapple market crash originating in Europe [Harou et al., 2017], and 2) when WT disadoption in one's network is low. Third, if correlated unobservables drive adoption decisions, they should also drive the disadoption decision. I show that this is not the case.

This paper makes both theoretical and empirical contributions to literature on social learning and technology adoption in developing countries. In terms of theoretical contributions, it allows for the possibility of disadoption by adopting farmers since it is possible that farmers do not arrive at their individual- and plot-specific true profitability prior to adoption. Target input models have been used, for example, by Foster and Rosenzweig [1995], Conley and Udry [2010a], and Bandiera and Rasul [2006] to explain how social learning influences technology adoption. These models implicitly assume away disadoption—learning increases profits only in expectation—which imposes strong, often unrealistic, assumptions of how learning potentially influences the adoption decision. Another contribution is that the model introduces elements of rational inattention to information in a context involving social learning. Thus, I merge insights from studies that demonstrate that farmers do not always pay attention to profit-enhancing information [Hanna et al., 2014] into a context that involves decisions about what to learn from peers. A final contribution is that farmers learn about the viability of adoption from original actions (adoption) in addition to subsequent actions (disadoption) that inform the success of the original action.[14] In terms of empirical contributions, this paper is first to analyse the effect of peer disadoption on the decision to use a new technology. Findings suggest that farmers use information from different types of peers in different ways. Recent evidence suggests that farmers are selective about the indi-

[14]Literature on the diffusion of actions (e.g., technology adoption) in society asks: what is the rate of diffusion of action a and when is it diffused across a population (see, for example Granovetter [1978], Banerjee [1992], Bikhchandani et al. [1992], Morris [2000], Young [2006], Centola [2010], Acemoglu et al. [2011], and Banerjee et al. [2013])? However, the literature has largely left unexamined the fact that action a might lead to action d, disadoption in my case. My model implies that diffusion rates might change when this is the case.

viduals from whom they glean the best information in their networks [Santos and Barrett, 2010, Beaman et al., 2015, Maertens, 2014, Tjernström, 2017]. Many of the same studies, however, identify information networks by asking farmers to whom they talk about agricultural activities. Results show asymmetric social influences stemming from WT and ST, which suggests that farmers use observable actions of others in the village to inform their own actions, even if these individuals would not otherwise be in one's information network. Given the difference between the role of WT and ST in other diffusion processes [Granovetter, 1973], it is surprising that empirical literature on diffusion of agricultural technologies approaches the problem only by suggesting that ST share more information than WT do with peers.[15]

Section 2.2 sets up a theoretical model by first distinguishing the role of the two objects of learning in a profit maximization problem. The latter part describes how a social network facilitates aggregation of information according to disparate learning heuristics. Section 2.3 describes the empirical context and data, and Section 2.4 the hazard model that estimates coefficients that inform tests generated by model implications. Section 2.5 describes results of the estimation, and conducts several robustness checks that further inform the mechanisms in the model. Section 4.6 discusses how network-based targeting policies intended to increase the rate of technology adoption might be reinterpreted through the lens of the model. Section 3.6 concludes and discusses policy implications that can be rethought in light of the interpretive lens of the model of social learning and technology adoption.

[15] Berg et al. [forthcoming] show that farmers do not share information about a new technology with socially distant ties, unless they are materially incentivised to do so. Thus, communication increases among WT when the cost of communication decreases through a subsidy. Additional evidence that corroborates that there are differences in information communicated among socially proximate ties is found in Feder and Savastano [2006], Chandrasekhar et al. [2016], and BenYishay and Mobarak [2014]. My argument is that information need not be shared directly for someone to be influenced by the actions of another.

2.2 Distinguishing Profitability Beliefs from Production Knowledge in an Adoption Decision

This section describes the learning process undertaken by an expected profit-maximizing farmer as he/she decides whether to allocate a portion of land to farming a new crop for the first time. Section 2.2.1 sets up the farmer's decision problem. Farmers hold profitability beliefs and can choose to acquire production knowledge (at a learning cost) as they contemplate the decision to adopt a new technology. Thus, this section analyses when the relationship between profitability beliefs and learning costs, the two objects of learning, leads to adoption of a new crop variety (proposition 1). Social learning and belief-updating dynamics are introduced in section 2.2.2, and I discuss the role of communication costs among STs and WTs along both objects of learning in section 2.2.3. Section 2.2.3 discusses how relationships that are characterised by risk-sharing might confound learning dynamics. I combine proposition 1 with social learning dynamics to articulate eight empirically testable model implications in section 2.2.4. Section 2.2.5 connects model implications to an empirical framework that can test these implications.

2.2.1 Model Setup

To introduce a farmer's decision problem, I combine elements of two well-established models [Foster and Rosenzweig, 1995, Munshi, 2004] by considering optimal investment when a farmer is selecting between two technologies: a new risky crop and a less-risky traditional variety. I begin with a static, single-period and single-agent setting. As in Munshi [2004], the traditional variety, y^{TV}, has constant per-acre profitability to distinguish it from the stochastic profitability of the new variety, y^{NV}. True profitability is drawn from a distribution unknown to the farmer. This induces uncertainty in the decision, which prompts each farmer to hold beliefs, q, over the average profitability of the new crop, $\mu(q)$ (profitability beliefs). Section 2.2.2 discusses dynamics in these beliefs. Initially, beliefs are drawn from a random variable, $\mathbf{q_0}$, that lies on the same domain as a second independent random variable that describes the belief level associated with the farmer's true profitability, $\bar{\mathbf{q}} \in [q_L, q_H]$. The lowest (highest) beliefs, q_L (q_H), generate guesses of low (high) average profitability, μ_L (μ_H) and $\mu_L < \mu(q) < \mu_H$, for all q. Since the distribution of $\mathbf{q_0}$ (and hence $\bar{\mathbf{q}}$) is unknown, each farmer uses only his/her unique draw, q, during calculations that inform adoption decisions.

The risk attributed to the new variety corresponds to the farmerâĂŹs production knowledge (as in Foster and Rosenzweig [1995]). An optimal or target-input use randomly fluctuates with some variance, which can be attenuated by engaging in learning.[16] Given A, the amount of land dedicated to the new crop, the farmer believes total profits from the new variety, $Y^{NV}(A)$, will be:

$$Y^{NV}(A) = A\mu(q) - (A(\theta - \tilde{\theta}))^2, \tag{2.1}$$

where θ is the input the farmer chooses to apply. Yields are maximised when the farmer chooses $\tilde{\theta} = \theta^* + \eta$; η is unknown at the time inputs are chosen, and is subject to iid stochastic shocks, η, with mean zero and known variance σ_η^2. The farmer holds unbiased regarding θ^* that are distributed $N(\theta^*, \sigma_\theta^2(e))$.[17]

Novel to my formulation is the farmer's choice of applying learning effort. Given the cognitive and physical challenge of learning a new production process, farmers can apply learning effort e to refine their model of optimal production. This implies that if $e > e'$,

[16] This assumption follows from the primary insight of Conley and Udry [2010a], in which the same farmers as those analysed in the current study change their fertiliser inputs toward more optimal targets after observing unexpectedly positive outcomes from peers' experiences.

[17] I assume that a farmerâĂŹs beliefs over θ^* are unbiased (as in Foster and Rosenzweig [1995]). It is intuitive that θ^* and $\bar{q}$ correlate. θ^* or $\bar{q}$ cannot be observed, and thus I cannot analyse the relationship between these two parameters empirically. I do, however, analytically address how learning about θ^* informs beliefs about $\bar{q}$ in section A.1.4.

then $\sigma^2_\theta(e) < \sigma^2_\theta(e')$. In the context of social learning, described in section 2.2.2, this effort corresponds to the cost of extracting communicable information from peers, as in Niehaus [2011].[18]

The farmer's choice problem is one of per-period profit maximization. Thus, during each period, he/she must choose A, the portion of total cultivable area, L, that will be used to cultivate the new crop. Total farm profits, π, are a function of profits from the traditional variety, $(L-A)y^{TV}$, and the new crop. Total profits, prior to incorporating learning costs, are:

$$\pi = (L-A)y^{TV} + Y^{NV}(A), \text{ such that } 0 \le A \le L. \tag{2.2}$$

To articulate conditions under which farmers choose to apply effort toward learning the nature of the production process, the cost of effort can take one of two values: $e = \bar{e} > 0$ if farmers choose to learn, and $e = 0$ otherwise. It is known that expected profit is maximised when farmers select input $\theta = \mathbb{E}[\theta^*]$. Thus, per-period expected profits are a function of $\sigma^2(e)$ and A, which allows me to articulate the farmer's maximization problem as:

$$\mathbb{E}[\pi] = \max_{A,e} \begin{cases} (L-A)y^{TV} + A(\mu(q) - A(\sigma^2_\theta(\bar{e}) + \sigma^2_\eta)) - \bar{e}, & \text{if } e = \bar{e}, \text{ and} \\ (L-A)y^{TV} + A(\mu(q) - A(\sigma^2_\theta(0) + \sigma^2_\eta)), & \text{if } e = 0. \end{cases} \tag{2.3}$$

Farmers select A, θ, and e to maximise expected profits during each period. To focus on the nature of social learning in subsequent sections, I assume myopic decision-making on the part of the farmer.[19] When there is an interior solution, (i.e., $A^* \in (0, L)$), first-order

[18] The implications of Hanna et al. [2014] further legitimates use of this assumption by suggesting that seaweed farmers often neglect data that can increase the profitability of a farming practice because of the cost of switching attention from one salient variable to another.

[19] Relaxing this assumption matters only when one can either predict the probability of future peer adoption (in a context with social learning) or ascertain the value of learning by doing. My focus is on the initial binary decision to adopt. Thus, learning-by-doing will only have the effect of increasing the probability of adoption *ex ante*, since beliefs regarding profitability are deterministic prior to adoption. By imposing that it is costly to learn (from others) about the production process, farmers are less likely to know the probability of peer adoption, thereby reducing the likelihood of strategic delay in adoption for the sake of learning from others.

conditions show that:

$$A^* = \frac{\mu(q) - y^{TV}}{2\gamma(e)} \text{ for } e = \{0, \bar{e}\}, \tag{2.4}$$

in which $\gamma(e) = \sigma_\theta^2(e) + \sigma_\eta^2$. Intuitively, this relationship states that the portion of land selected for the new variety increases as a farmer's profitability beliefs increase, and decreases when he/she has less knowledge of optimal cultivation processes ($e = 0$ relative to $e = \bar{e}$).

Prior to analysing the ways in which model parameters influence adoption of the new crop, I make one final assumption: farmers are unwilling to adopt the new crop on an infinitely small segment of their land. This assumption reflects the nature of pineapple cultivation; there is significant sunk costs associated with transforming a plot of land into a pineapple field. Pineapples require suckers to grow, which renders the field unusable for any other purpose once the suckers are planted. Additionally, suckers take 6 to 24 months to bear fruit, which presents an opportunity cost that cannot be salvaged. Therefore, adoption of the new crop takes the shape of a binary variable of form:

$$a = \begin{cases} 0, \text{if } A^* < \bar{A}, \text{ and} \\ 1, \text{if } A^* \geq \bar{A}.^{20} \end{cases} \tag{2.5}$$

A farmer's decision to adopt is now a function of beliefs regarding the profitability of the new crop, $\mu(q)$, and learning cost $\bar{e}$. I observe one of three outcomes for each farmer: adoption with learning effort ($a = 1, e = \bar{e}$), adoption without learning effort ($a = 1, e = 0$), or no adoption ($a = 0, e = 0$).[21] Proposition 1 asserts that farmer selection into these three outcomes is a function of $\mu(q)$ and $\bar{e}$.

[20] Certainly, $a = A^*$ if $\bar{A} \leq A^* < L$ and $a = L$ if $A^* \geq L \geq \bar{A}$. Unfortunately, the data do not allow me to analyse a continuous adoption decision, which motivates the binary choice variable in the model.

[21] No adoption with learning ($a = 0, e = \bar{e}$) is disqualified by construction in the static setting.

Proposition 1 (Characterizing Criteria for Adopting a New Crop) *Consider the case in which $\bar{A}^{NE} < L^{LE}$, where $L^{LE} = 2\gamma(\bar{e})L + y^{TV}$.*[22] *The farmer's adoption choices*

$\bar{A}^{NE}$ ($\bar{A}^{LE}$) is the lowest value for profitability beliefs at which adoption without (with) learning is preferable to non-adoption. When $\mu(q) < \bar{A}^{NE}$ ($\mu(q) < \bar{A}^{LE}$), adoption without (with) learning effort is ***infeasible***. L^{LE} (L^{NE}) is a profitability belief level at which a farmer reaches a corner solution, $A^* = L$, if the farmer applies (no) learning effort. A formal discussion and proof appears in appendix A.1.1.

The proposition suggests that a farmer's adoption status is known if his/her profitability beliefs and learning costs are also known. Thus, much of this proposition can be described intuitively in terms of the perceived opportunity costs of learning, as depicted in figure 2.4. The farmer will not adopt when adoption with learning is infeasible. When adoption with learning is feasible (i.e., $\mu(q) \geq \bar{A}^{LE}$), the farmer adopts if the opportunity costs of learning are too high. This is intuitively represented by the dark region in the figure, where $\mu(q) > \bar{A}^{LE}$; as learning costs, $\bar{e}$, increase beyond $\bar{e}_1$, and profitability beliefs lie between $\bar{A}^{LE}$ and $\bar{A}^{NE}$, only farmers with relatively low learning costs ($\bar{e} < \bar{e}_4$) adopt the new crop. Once adoption without learning is feasible, the farmer adopts the new crop no matter what; the graph does not contain any dark areas when $\mu(q) > \bar{A}^{NE}$. This reflects the fact that the farmer has extreme beliefs over the profitability of the new crop: $\mu(q)$ is very large relative to y^{TV}.

Although the farmer will adopt the new crop under these extreme beliefs, he/she might apply learning effort in this region. The learning decision depends on whether the farmer

[22]Consequently, $L^{NE} = 2\gamma(0)L + y^{TV}$. Notice, $\bar{A}^{LE} < \bar{A}^{NE} < L^{NE}$ and $\bar{A}^{LE} < L^{LE} < L^{NE}$ by definition. This condition suggests that as $\mu(q)$ increases, adoption without learning becomes feasible before the farmer reaches a corner solution, $A^* = L$, when applying learning effort, which seems reasonable and limits the relationship between $\gamma(0)$ and $\gamma(e)$, such that $1 > \frac{\gamma(e)}{\gamma(0)} > \frac{\bar{A}}{L}$.

has reached the corner solution when applying learning effort. If he/she has not reached the corner solution, the opportunity costs of learning must include the relative value of learning over not learning. This is represented by the relationship between $\mu(q)$ and $2\sqrt{\bar{e}\frac{\gamma(\bar{e})\gamma(0)}{\gamma(0)-\gamma(\bar{e})}}$, the opportunity cost of learning.[23] The opportunity costs of learning decreases as the benefit of learning $(\gamma(0)-\gamma(\bar{e}))$ increases. If the increase in precision is cheap enough to obtain ($\bar{e} < \bar{e}_2$ or $\bar{e} < \bar{e}_3$ under some conditions on $\mu(q)$), the opportunity costs of learning are low, and the farmer desires this precision. Otherwise, gains from adoption are too high to pass up, even if the opportunity costs of learning are high. When a farmer has reached a corner solution with learning, the opportunity costs of learning increase relative to not learning; if beliefs are extreme enough that farmers think the new technology substantially outperforms the traditional variety, added precision is merely an inconvenience that is not worth the added learning effort.

2.2.2 Social Learning

This section describes how social influences alter profitability beliefs and learning effort in a dynamic setting. I argue that beliefs can be thought of as a construct of the farmer's mind, the hypothetical subjective value placed on the average outcome associated with farming a new crop. This belief is not falsifiable *ex ante*, given its subjective nature, and can be thought of as a function of a farmer's initial type and the role of peer influence on the evolution of these beliefs.[24] Knowledge about a production process can be implemented in practice, and represents one's understanding of a falsifiable model of a production practice. When one is

[23] $\mu(q) = 2\sqrt{\bar{e}\frac{\gamma(\bar{e})\gamma(0)}{\gamma(0)-\gamma(\bar{e})}}$ is the line separating the light grey area from the dark grey area in figure 2.4, when $\mu(q) < L^{LE}$.

[24] An analogy is a belief in the continued progress of a soul following its departure from a body. One's type can reveal whether one believes in such an afterlife. However this belief is not likely to be objectively falsifiable *ex ante* (i.e., before death).

equipped with scientific capabilities (e.g., the capacity to test a theory), additional trials and observations assist with refining the theory. I outline a two-stage learning process in which the two objects of learning are tied to different learning heuristics. Profitability beliefs are cheap to update, so they are the first object of learning. I argue that an appropriate heuristic for belief-updating is a DeGroot updating process (DUP), whereas Bayesian learning principles provide a more appropriate heuristic for acquiring production knowledge. A DUP assumes the existence of a population with an initial distribution of probability beliefs, and an interaction structure, perhaps represented by a social network. In this context, agents update beliefs in a DeGroot fashion each period by moving closer to the weighted average of peers' beliefs.

Production knowledge requires learning effort, and thus farmers will choose to acquire it during a second stage of learning if they believe that the associated action is relatively profitable, on average. As an object of learning, production knowledge is refined through analysis of multiple trials. I impose learning effort to be a decreasing function of opportunities to gain insights from peer experiences producing the new crop. When this assumption is applied to the model, I generate the same comparative statics as Foster and Rosenzweig [1995], who use Bayesian updating to refine values of σ_θ^2 from peer experiences. Generally, the quality inherent in Bayesian learning, in which additional draws of a parameter lead me closer to a true parameter, is desirable when the object of learning is attributed to a process or action that can be understood or applied with degrees of precision.

There are several advantages to specifying updating and learning heuristics this way. First, as Chandrasekhar et al. [2015] argue, unlike Bayesian learning, DeGroot updating need not require that populations of agents converge to the same belief. In practice, this means that some agents might believe that the new crop is profitable while others do not. Second, it is desirable for farmers to form beliefs around profitability in a (computationally) simple manner prior to investing in a (computationally) intense Bayesian learning paradigm.[25] A farmer is unlikely to invest scarce mental resources, through learning effort, in cultivation of a new crop if it is unprofitable in expectation. This distinguishes a DUP from most forms of Bayesian learning, in which each observation helps the learner identify the true parameter of interest through learning. Third, disadopters likely have low beliefs regarding the profitability of the new crop. A DUP generates a comparative static in which this low belief is reflected in the weighted average that each individual generates. However, when a farmer is considering whether to apply learning effort, each one of his/her peers' farming experiences, whether a current adopter or disadopter, can lead to increased understanding of the best production practices used in cultivating the new crop. Peer disadoption in a social learning model that uses only Bayesian learning heuristics cannot decrease one's likelihood of adoption, which is a peculiar implication.

Modified DeGroot Updating and Profitability Beliefs

Prior to introducing DUP, additional notation is required. First, introduce N individuals into a discrete dynamic setting, in which $t = \{0, 1, 2, \ldots\}$, and index each variable in section 2.2.1 with it when the variable is used to reference an individual, i, and time period t. Next, I define a function, $\mu_{it}(q_{it})$, that relates profitability beliefs to expected profitability:

$$\mu_{it}(q_{it}) = q_{it}(\cdot)\mu_h + [1 - q_{it}(\cdot)]\mu_l \text{ s.t., } \mu_h > \mu_l \tag{2.6}$$

in which farmers weigh whether the mean profits will correspond to high or low profits, $\mu_h > y^{TV}$ or $\mu_l < y^{TV}$, by probability $q_{it}(\cdot)$, respectively $1 - q_{it}(\cdot)$, at time t.

[25]In the same paper, Chandrasekhar et al. [2015] provide evidence that a DUP predicts belief updating more accurately than Bayesian learning does. However, they do not delineate objects of learning like this paper does. A distinguishing feature of the present discussion is its claim that the heuristic that one applies to an object of learning depends on its qualities.

To introduce DUP, I use an interaction structure among the individuals, and allow beliefs in the high profit state, q_{it}, to evolve according to the average beliefs of others with whom one interacts. Thus, $\mathbf{G'}$ characterises an interaction pattern (adjacency matrix) on a row-normalised $N \times N$ social network (each row sums to one), in which each cell G'_{ij} represents the weight i places on interactions with j for $i, j = \{1, 2, \ldots, N\}$.[26] Let time-denoted profitability beliefs be characterised by an N-dimensional vector of probabilities, $\mathbf{q_t} = (q_{1t}, \ldots, q_{it}, \ldots, q_{nt})$, where $q_{it} \in [0, 1]$ for each period t [Jackson, 2008]. DeGroot updating implies that beliefs are updated over time such that $\mathbf{q_t}(\mathbf{G'}, \mathbf{q_{t-1}}) = \mathbf{G'}\mathbf{q_{t-1}} = (\mathbf{G'})^t\mathbf{q_0}$ and $\mathbf{q_t} \in [0, 1] \times N$.[27] $\mathbf{q_0}$ is drawn from an initial distribution of beliefs. I now impose that this distribution be restricted to satisfy the condition that beliefs be greater than zero or less than 1. However, beliefs might be contradicted when plans are actualised. When farmers adopt the new crop, they can rely on their own evidence to inform their beliefs regarding the profitability of the new crop in their circumstance. When the true belief is not to their liking, this can also result in disadoption. In a belief-updating framework, this suggests that a farmer who has yet to adopt the new crop can update profitability beliefs based on peers' beliefs, peers' actions (adoption), or the consequences of peers' actions (disadoption).

I need the additional notation to represent a modified DUP that reflects the manner in which beliefs evolve after actions are taken. First, let $\mathbf{T}$ indicate the vector of first periods of adoption in the population. T_i indicates the period during which farmer i adopts. $\mathbf{a_t}$ is a vector of adoption status for the period—$a_{it} = 1$ if i has adopted at time t, and zero otherwise. Thus, $a_{iT_i} = 1$ implies that $a_{iT_i-1} = 0$. Next, D_i (vector $\mathbf{D}$) indicates the analogous period

[26] Later, I also use the binary adjacency matrix during analysis, which I label $\mathbf{G}$. Thus $\mathbf{G'}$ multiplied by a vector reflects the network-weighted average of the vector for each individual, and $\mathbf{G}$ reflects the network-sum of the vector when each cell in $\mathbf{G}$ can take either value zero or 1, depending on whether a link exists between i and j.

[27] During period t, each agent, i, is weighing interaction $G'_{ij} \in [0, 1]$ (such that $\sum_{j=1}^{N}[G'_{ij}] = 1$) according to the influence of agent j's period $t-1$ beliefs on agent i. Thus, at time t, $q_{it} = \sum_{j=1}^{N} G'_{ij} q_{j,t-1}$. Agent i can weigh the influence of each peer, j, including him/herself ($\mathbf{G'}_{ii}$), however he likes as long as all weights add to 1.

during which disadoption takes place for each farmer $i \in N$. $d_{it} = 1$ if a farmer disadopted the new crop during or prior to period t, and zero otherwise (i.e., $t \geq D_i$.)[28] A modified DUP of profitability beliefs can be represented by the function:

$$q_{it}(\mathbf{G'}, \mathbf{q_{t-1}}|\mathbf{T}, \mathbf{D}) = \begin{cases} \sum_{j=1}^{N}[G'_{ij}q_{j,t-1}] \text{ if } 0 < t \leq T_i \\ \lambda^{t-T_i}q_{iT} + (1-\lambda^{t-T_i})\bar{q}_i \text{ if } T_i < t < D_i \\ \lambda^{D_i-T_i}q_{iT} + (1-\lambda^{D_i-T_i})\bar{q}_i \text{ if } D_i \leq t \end{cases} \tag{2.7}$$

in which $\bar{q}_i$ represents the belief associated with the true profitability for farmer i, and λ is a decay parameter such that $0 < \lambda < 1$, which indicates the speed at which a farmer converges on the true profitability after adopting the new crop.[29] A non-adopter updates his/her beliefs in a typical DeGroot fashion, while others rely on their own experiences to update their beliefs. For adopters, dynamics associated with q_{it} depend on whether they overestimated or underestimated $\bar{q}_i$ at the moment of adoption. If there is overestimation (underestimation), $\bar{q}_i$ is less than (greater than) q_{iT}, and beliefs decrease (increase) over time. For disadopters, $\bar{q}_i$ is always less than q_{iT}, and beliefs decrease until the period of disadoption, after which beliefs remain stuck (constant) during all future periods.

Of particular interest is the farmer who has yet to make a decision regarding whether to adopt the new crop. $\mu_{it}(q_{it})$ is one of two variables that are inputted into a mapping of the adoption decision. Thus, a question central to this analysis is: how do i's profitability beliefs change when $t < T_i$ and a network contact adopts or disadopts the new crop? First, $\frac{\partial q_{it}}{\partial q_{j,t-1}} = G'_{ij}$. This states that i's beliefs change in proportion to j's beliefs according to weight G'_{ij}, though additional information is needed to know whether j causes an increase or decrease in i's beliefs. To examine this, I analyse the sign of changes in j's beliefs over

[28] $d_{it} = 1$ if for some $t' < D_i$, $a_{it'} = 1$, but $a_{iD_i} = 0$. Thus, d_{it} holds information about the history of adoption status for individual i if i is not using the new variety at time t. I assume no re-entry following disadoption.

[29] $\lim_{t\to\infty}[\lambda^{t_i-T_i}q_{iT} + (1-\lambda^{t_i-T_i})\bar{q}_i] = \bar{q}_i$

time as a function of his/her adoption or disadoption status.[30]

I take advantage of the fact that *once a farmer acts, his/her beliefs are no longer a function of his/her network's beliefs.*[31] Thus, I can understand the degree to which the act of j's transition to adoption or disadoption status shifts q_{it} conditional on knowing G'_{ij}. i's contacts can be divided into five categories: 1) peers who disadopt during period $t-1$ ($D_j = t-1$), 2) peers who adopt during period $t-1$ ($T_j = t-1$), 3) peers who adopted prior to period $t-1$ ($T_j < t-1 < D_j$), 4) peers who disadopted prior to period $t-1$ ($D_j < t-1$), and 5) all other peers who have yet to adopt. I decompose changes to the beliefs of a farmer who has yet to adopt using:

$$\Delta q_{it} = \mathbf{g_i'}\Big[\overbrace{\Delta \mathbf{q_{t-1}} \cdot \mathbb{1}(\mathbf{D} = t-1)}^{<0} + \overbrace{\Delta \mathbf{q_{t-1}} \cdot \mathbb{1}(\mathbf{T} = t-1)}^{\geq 0} \tag{2.8}$$

$$+ \underbrace{\Delta \mathbf{q_{t-1}} \cdot \mathbb{1}(\mathbf{D} < t-1)}_{=0} + \underbrace{\Delta \mathbf{q_{t-1}} \cdot \mathbb{1}(\mathbf{T} < t-1 < \mathbf{D})}_{\approx 0} \tag{2.9}$$

$$+ \underbrace{\Delta \mathbf{q_{t-1}} \cdot \mathbb{1}(\mathbf{T} > t-1)}_{\text{“Indirect Effect”} \lesseqgtr 0}\Big] \text{ if } t < T_i, \tag{2.10}$$

where $\Delta \mathbf{q_t} = \mathbf{q_t} - \mathbf{q_{t-1}}$; $\mathbf{g_i'}$ is the i^{th} row of the adjacency matrix $\mathbf{G'}$ used to update beliefs, and indicator variable $\mathbb{1}$ is a vector equal to 1 if farmers' adoption or disadoption periods correspond to the term inside the brackets, and zero otherwise.

The effect of peers in category one should have a negative effect on i's beliefs because their beliefs decreased during the previous period, prompting disadoption. Although it is possible

[30] To know the full extent of these dynamics, I could start with knowledge of the initial distribution of beliefs, $\mathbf{q_0}$, and the true profitability of each farmer, $\bar{\mathbf{q}}$, and track the influence of each individual's beliefs on others given interaction structure $\mathbf{G'}$. It is, however, highly unlikely that these components can be observed empirically in a natural setting, rendering such analysis excessive for the present application. This is one reason DeGroot updating has received more theoretical than empirical attention (Chandrasekhar et al. [2015] an exception), and hence is more concerned with the convergence properties of learning under different network and belief configurations (see Jackson [2008] for such a discussion).

[31] Very little systematic attention has been paid to processes that lead to disadoption. However, research to date suggests that disadoption is driven by experiences with the technology itself [Neill and Lee, 2001, Moser and Barrett, 2006, Wendland and Sills, 2008, Zeitlin, 2011], not peer influence.

for farmers to adopt the new variety following a decrease in their beliefs (possible only if their learning costs decrease during the same period), it is highly unlikely, prompting me to assume that the effect of a peer in category two is positive. Peers in category three disadopted prior to period $T-1$, and are no longer updating their beliefs; their contribution to a change in i's beliefs is therefore zero. Peers in category 4 are moving closer to beliefs associated with the true profitability. However, since true profitability is distributed randomly, farmers' beliefs could be either increasing or decreasing during each period after adoption. Without the ability to separate increasing from decreasing beliefs, I assume that the change to beliefs from this fourth category approximates zero. The fifth term includes all farmers who have yet to adopt the new crop but whose beliefs are changing through interactions with peers—the indirect effect.'[32] This effect might contribute to an increase or decrease in i's beliefs, and is important to control for when discussing empirical specifications that test the effect of belief dynamics on adoption.

Network Influence on Learning Costs

If beliefs suggest the potential for greater profits were one to switch to the new crop, farmers might consider applying effort to learning about the production process, the second object of learning. Farmers who apply learning effort are doing so to refine their understanding of the optimal target input process from a distribution of $N(\theta^*, \sigma^2_\theta(0))$ to $N(\theta^*, \sigma^2_\theta(\bar{e}))$. In similar target–input learning applications [Foster and Rosenzweig, 1995, Bandiera and Rasul, 2006, Conley and Udry, 2010a], $\sigma^2(e)$ is a decreasing function of the number of trials a farmer

[32] They are indirect in the sense that they refer to changes in i's beliefs through j that is in effect a function of the change in the weighted average of $t-2$ beliefs among j's networks, which are a function of the change in the weighted average of $t-3$ beliefs of these farmers' networks (and so on). This indirect effect is equal to $\mathbf{g_i'} \sum_{k=2}^{t} [\mathbf{G^{k-1}} \cdot \mathbf{\Delta q_{t-k}} \cdot \mathbb{1}(\mathbf{D} = t-k) + \mathbf{G^{k-1}} \cdot \mathbf{\Delta q_{t-k}} \cdot \mathbb{1}(\mathbf{T} = t-k)]$, if $t > 2$ and I drop the null effects in equation 2.8. In an empirical context, there is a k at which differences in $\mathbf{G^{k-1}}$ among individuals in a sample become negligible, and the ensuing vector cross product produces effects indistinguishable from time and network fixed effects.

can observe. I generalise this assumption by allowing the cost of learning to be a decreasing function of learning opportunities, S_i. These opportunities include the insights one can gain from peers' trials, and direct participation in training provided by extension agents, an NGO, or business partner. The costs of learning are also a function of the qualities of the subject who is learning, Q_i. These qualities can be thought of as scientific capabilities conditional on the existence of opportunities for learning (e.g., having access to trials to analyse), and increases in Q_i decrease the costs of learning.[33]

I formalise these assumptions. Allow $e(S_{it}, Q_i) = f(S_{it}, Q_i)$ and $f(\cdot)$ is twice continuously differentiable such that $\frac{\partial f}{\partial S_{it}} < 0$ and $\frac{\partial^2 f}{\partial S_{it} \partial Q_i} > 0$. The second differential relationship implies that learning costs are decreasing at an increasing rate when both learning opportunities and subject qualities are increasing. Think of a highly capable individual with many opportunities for learning. To ensure that I capture the role of social learning through S_{it}, I allow $S_{it} = \sum_{j \neq i}^{N} G_{ij}(a_{jt} + d_{jt}) + O_{it}$, where G is a network adjacency matrix with cells $G_{ij} = 1$ if i is linked to j, and zero otherwise. O_{it} represents the opportunities to learn about production processes outside of one's peer network.[34] Learning opportunities can come from either adopters of the new crop or disadopters; both have relevant experiences from which one can draw to refine understanding of the production process.

[33]Additional ways of thinking of Q_i include the ability to formulate hypotheses, measure and capture relevant variables, design and set up experiments, link data to hypotheses, make appropriate logical inferences from tests of data, etc. I am conceiving scientific capabilities as a powerful form of complementary knowledge, as Niehaus [2011] discusses.

[34]If $e = Q_i^{-1}(\sum_{j \neq i}^{N} G_{ij}(a_{jt} + d_{jt}) + O_{it})^{-1}$, which is a special case that satisfies my assumptions, abusing notation $\sigma^2_{\theta,it}(e) = \frac{1}{\sigma^2_{\theta,i0} + \beta(e)^{-1}}$ is similar to the Bayesian updating formulation in Foster and Rosenzweig [1995], and also satisfies assumptions on $\sigma^2_{\theta}(e)$.

2.2.3 The Social Influence of Friends, Acquaintances, and Family

I assume above that each farmer can observe the beliefs of each other member in his/her peer group through a DeGroot process, though it is unlikely that this is true. Similarly, the cost of communication among friends or family members is likely lower than the cost of similar communication among acquaintances. Thus, a principle applied to the heuristic for both objects of learning is that they are dependent on the ease of communicating information across peers. Since beliefs are highly private and farming experiences are highly contextual, it is reasonable to assume that the degree to which farmer i extracts information from farmer j depends on the quality of relationship between i and j. Specifically, *information is more easily communicated with socially proximate strong ties (ST) than with socially distant weak ties (WT).*[35]

With respect to learning effort, this relationship is straightforward. First, allow G to be composed of two adjacency matrices, G^{ST} and G^{WT}, representing ST and WT, respectively (i.e., $G_{ij}^{ST} + G_{ij}^{WT} = G_{ij}$, and if $Gij^{ST} = 1$, $Gij^{WT} = 0$, and vice versa.). The logic above suggests:

$$\frac{\partial f}{\partial S_{it}^{ST}} < \frac{\partial f}{\partial S_{it}^{WT}} < 0 \text{ such that } S_{it}^{k} = \sum_{i \neq j}^{N} G_{ij}^{k}(a_{jt} + d_{jt}) \text{ for } k = \{ST, WT\}.$$

This relationship implies that the cost of learning effort decreases more when a ST adopts a new crop than when a WT adopts a new crop. This assumption is intuitive, but is also supported by empirical evidence. Berg et al. [forthcoming] suggest that material incentives increase knowledge transmission among WTs, but have no effect on knowledge transmission among STs.

[35] Success in farming depends on relatively unobservable factors (both to the econometrician and peers), such as labour and credit availability, knowledge of inputs used, soil fertility, planning ability, etc., all of which vary to a great extent across households and even individual farmers within households. This formulation assumes that the degree to which these factors are unobservable among peers depends on their social distance.

Belief-updating requires more careful thinking. First, assume that q_{jt} is only communicated to i when $G_{ij}^{ST} = 1$. The relationship characterised in equation 2.8 then holds true. Individual i will know the direction of change in j's belief at the moment of adoption when they are STs, but the relationship is still ambiguous from an econometrician's perspective. The only unambiguous relationship that both the researcher and farmer i both know is that j's disadoption resulted from a decrease in beliefs.

Assume that q_{jt} is unobservable to i when $G_{ij}^{WT} = 1$, but a_{it} and d_{it} are. This is a reasonable assumption because pineapple is a perennial sucker crop, which can be easily observed to be growing in one's field. Similarly, when one disadopts pineapple, the contrast that stems from observing a field full of planted suckers to one without any is stark. Finally, it is generally known which fields belong to STs, and hence fields belonging to WTs are known by elimination.

Due to the act of j's disadoption, i knows with certainty that during period $t = D_j$, individual j's profitability beliefs are less than when $T_j < t < D_j$. Without knowing j's learning costs, i knows that at the moment of adoption, q_{jT_j} had to be above some minimal threshold such that $\mu_{jT_j}(q_{jT_j})$ rendered the decision to adopt feasible for individual j. Beliefs move toward the true profitability at a rate proportional to the decay rate $(1 - \lambda_j^{t-T_j})$. Since i does not observe a WT's gradual transition from q_{jT_j} to $\bar{q}_j^D$, he/she treats j's disadoption as a signal that provides information on a sequence of decreases in profitability beliefs.

How can this reaction be operationalised through i's perceptions of j's beliefs? Since $\bar{\mathbf{q}}$ is distributed randomly in a population, I allow i to form expectations over j's beliefs conditional regarding whether j is an adopter, disadopter, or neither. However, i does not know the true distribution of $\bar{\mathbf{q}}$, which prompts a naïve approach to forming expectations. First, assuming that i forms expectations over $\bar{\mathbf{q}}$ as though it is a random variable, this implies that $q_{jt} = \mathbb{E}[\bar{\mathbf{q}}_j|a_{jt} = 0, a_{it} = 0] = \mathbb{E}[\bar{\mathbf{q}}_\mathbf{N}]$ when $t < T_j$. When j adopts the new variety, i infers that j's beliefs are similar to the expected value of profitability beliefs of an adopter (i.e., i perceives $q_{jt} = q_{jT_j} = \mathbb{E}[\bar{\mathbf{q}}_\mathbf{j}|a_{jt} = 1, a_{it} = 0] = \mathbb{E}[\bar{\mathbf{q}}_\mathbf{A}]$ for all t such that $D_j > t \geq T_j$). The analogue for j as a disadopter is similar, and i perceives $q_{jt} = q_{jD_j} = \mathbb{E}[\bar{\mathbf{q}}_\mathbf{j}|d_{jt} = 1, a_{it} = 0] = \mathbb{E}[\bar{\mathbf{q}}_\mathbf{D}]$ for all $t \geq D_j$. The values of $\mathbb{E}[\bar{\mathbf{q}}_\mathbf{N}]$, $\mathbb{E}[\bar{\mathbf{q}}_\mathbf{A}]$, and $\mathbb{E}[\bar{\mathbf{q}}_\mathbf{D}]$ are likely to vary by farmer i, though I assume that $\mathbb{E}[\bar{\mathbf{q}}_\mathbf{D}] < \mathbb{E}[\bar{\mathbf{q}}_N] < \mathbb{E}[\bar{\mathbf{q}}_\mathbf{A}]$.

The Confound of Resource-Pooling

Social influences need not operate through a learning channel alone (see Besley [1995] for a discussion of informal risk-sharing in developing countries). Consider a situation in which i and j pool resources and consider each others' wealth (land size) when making decisions. Since the optimal choice of land depends on an upper land size bound, L, a resource-pooling (RP) arrangement increases the upper bound ($L^{RP} = L_1 + L_2$) above a limiting threshold for adoption, such as A^{NE} or A^{LE}. Thus, only one of i or j will adopt. I impose that i will adopt to understand i's influence on j's adoption decision. Assuming that i's adoption influences j's beliefs, and certainly decreases j's learning costs, j might now be in a position to adopt the new crop individually, given the previous discussion in this section. Due to portfolio balancing, however, j's probability of adoption is non-increasing, and possibly decreasing, in i's adoption. These effects attenuate the learning effects over the same links.

2.2.4 Testable Implications and a Basic Empirical Approach

Adoption and disadoption status are easily observable, but beliefs and production knowledge are more difficult to measure. Thus, I analyse changes to adoption status by understanding how it is influenced by changes in beliefs and learning costs through peers' adoption and disadoption decisions. I do this by considering comparative statics around the boundary conditions represented in corollary 1, and ask: how do changes in the adoption and disadoption patterns of one's social networks influence the adoption decision?

First, the boundary generated by proposition 1 between $a = 0$ and $a = 1$ can be separated into three regions along the profitability belief dimension: 1) the region in which adoption with learning is infeasible ($\mu(q) < \bar{A}^{LE}$), the region in which adoption without learning is feasible ($\mu(q) \geq \bar{A}^{NE}$), and the region in between ($\bar{A}^{LE} \leq \mu(q) < \bar{A}^{NE}$). The following corollary articulates the conditions on profitability beliefs and learning costs that identify the period of adoption, T_i, for farmer i:

Corollary 1 *Let $P(t = T_i)$ equal 1 if $t = T_i$ and 0 if $t < T_i$, then*

$$P_i(t = T_i | \mathbf{T_{-i}}, \mathbf{D_{-i}}) = \begin{cases} 0, & \textit{if } p_{it,1}(S_{it}, \mathbf{q_t}) = \mu_{it}(q_{it}(\cdot | \mathbf{T_{-i}}, \mathbf{D_{-i}})) - \bar{A}^{LE} \leq 0; \\ 0, & \textit{if } p_{it,2}(S_{it}, \mathbf{q_t}) = \mu_{it}(q_{it}(\cdot | \mathbf{T_{-i}}, \mathbf{D_{-i}})) - 2\sqrt{\bar{e}(S_{it})\gamma(e)} + y^{TV} \leq 0 \textit{ and} \\ & \quad \bar{A}^{LE} < \mu_{it}(q_{it}(\cdot | \mathbf{T_{-i}}, \mathbf{D_{-i}})) < \bar{A}^{NE}; \\ 0, & \textit{if } p_{it,3}(S_{it}, \mathbf{q_t}) = \mu_{it}(q_{it}(\cdot | \mathbf{T_{-i}}, \mathbf{D_{-i}})) - \bar{A}^{NE} \leq 0; \\ 1, & \textit{otherwise.} \end{cases} \tag{2.11}$$

Each function $p_{it,k}$ denotes the required criteria for adoption in each of the three domains (along the profitability beliefs axis) described above. Adoption ensues when an indifferent farmer who lies on, or near, the boundary in figure 2.5 moves to a point in the parameter space above the boundary line. Otherwise, the farmer remains a non-adopter.

Testing the Production Knowledge Channels

I begin with a discussion of model implications that connect changes in peer adoption to adoption decisions by influencing production learning. To clarify notation, $\Delta P(T') = P(t_i = T_i|\mathbf{T_{-i}}, \mathbf{D_{-i}}) - P(t_i = T_i|\mathbf{T'_{-i}}, \mathbf{D_{-i}})$, which represents the change in i's status as network peers switch from non-adoption ($\mathbf{T'_{-i}}$) to adoption ($\mathbf{T_{-i}}$) status.[36] If a peer's action induces adoption in i, $\Delta P(T') = 1$.

Model Implication 1 *When i believes that adoption with learning is infeasible, ($\mu_{it}(q_{it}) \leq \bar{A}^{LE}$), there is no point at which the application of learning effort will induce a farmer to adopt, and $\frac{\partial p_{it}^k}{\partial S_{it}^k} = 0 \Rightarrow \Delta P = 0$.*

This is an intuitive yet previously untested result. If it is costly to acquire production knowledge and there is no benefit to acquiring it, even events that facilitate the opportunity to gain production knowledge, such as peer adoption, will be unsuccessful at inducing adoption. If a farmer resides at point A in figure 2.5, and his/her learning costs decrease (horizontal movements to the left), he/she is not induced into the region of the graph that lies above $P_i(t = T_i|\mathbf{T_{-i}}, \mathbf{D_{-i}})$. However, as the farmer's parameter combination moves to the right of A along the boundary line and beyond the first kink point ($\bar{e}(S_{it}) = \bar{e}_1$), changes to learning costs induce adoption.

Model Implication 2 *When adoption with learning is feasible, an increase in peers with new crop experience induces adoption: $\frac{\partial p_{it,2,3}}{\partial S_{it}^k} > 0 \Rightarrow \Delta P = 1$.*

This stems from the fact that additional peers with experience facilitate production learning, thereby decreasing learning costs and inducing adoption when it is feasible (with learning).

[36] The subscript in T_{-i} indicates the vector of the timing of adoption for each individual in the network other than i.

Peers with whom one communicates more effectively decrease learning costs more than other peers do. As the farmer's parameter combination moves to the right of point B in figure 2.5, ST adoption induces adoption in i, even when a similar increase in the adoption of WTs does not.

Model Implication 3 *Strong ties are better able to induce adoption through the learning channel than WTs are. Assume i's profitability belief is such that* $q_{it} = q_B/$*, and he/she is positioned at point B in figure 2.5. There then exists some point* $\bar{e}' > \bar{e}_B$ *such that* $\frac{\partial p_{it,2,3}}{\partial S_{it}^{S}T} > 0 \Rightarrow \Delta P(T') = 1$*, but* $\frac{\partial p_{it,2,3}}{\partial S_{it}^{WT}} > 0 \nRightarrow \Delta P(T') = 1$*.*

A subject's ability to learn is also a function of his/her qualities. Defined in section 2.2.2, i is better able to take advantage of opportunities for learning when he/she is endowed with (or has developed) qualities that enable him/her to more easily gain insights from others' experience. Similar to model implication 3, this implies that the learning effect is magnified when a subject's learning qualities, Q_i, are high.

Model Implication 4 *Farmers with more developed scientific capabilities magnify the learning effect in* $\frac{\partial p_{it,2,3}}{\partial S_{it}^{k}}$*. Thus, if* $Q_i > Q_i'$*,* $\frac{\partial p_{it,2,3}}{\partial S_{it}^{k}(Q_i)} < \frac{\partial p_{it,2,3}}{\partial S_{it}^{k}(Q_i')}$*.*

This effect and the effect discussed in model implication 3 are represented by the blue arrows in figure 2.5. The direction of change is the same as the horizontal white arrows, but the magnitude of change is much larger. Increases in learning opportunities for capable learners are more effective at inducing adoption than similar increases for less capable learners are.

Testing the Profitability Belief Channels

I now consider ways in which adopters and disadopters influence i's beliefs regarding the profitability of a new crop. I analyse changes to beliefs due to changes to the beliefs of STs, and then effects stemming from observable behaviours of WTs and comparisons between weak and ST effects. If j is a ST and disadopted during period $t-1$, his/her beliefs decreased during $t-1$, and this decreases i's profitability beliefs during period t. If j adopted during period $t-1$, it is possible that this was due to an increase in j's beliefs, which increase i's beliefs.[37]

To assist with the formulation of model implications, I again use the notation that $\Delta P(T') = 1$ if changes to network adoption status induces i to adopt. However, I also need to understand whether j's disadoption causes i to delay adoption. Thus, $\Delta P(D') = P(t_i = T_i|\mathbf{T_{-i}}, \mathbf{D_{-i}}) - P(t_i = T_i|\mathbf{T_{-i}}, \mathbf{D'_{-i}}) = 1$ if i would have adopted during period $t = T_i$ (when disadoption is characterised by $\mathbf{D_{-i}}$) were it not for period $t-1$ switches from adopter to disadopter status along the network ($\mathbf{D_{-i}}'$ such that $\mathbf{D_{-i}}' \leq \mathbf{D_{-i}}$). These switches prompt i to delay adoption to a period $T_i' > T_i$. $\mathbf{g_i}' \cdot \mathbf{d}_{t-1} = \mathbf{g_i^{WT\prime}} \cdot \mathbf{d}_{t-1} + \mathbf{g_i^{ST\prime}} \cdot \mathbf{d}_{t-1}$ represents the cross-product of the number of disadopters during period $t-1$ by the respective weights each receives from i in his/her calculation of beliefs during each period. The analogous variable for adopters is $\mathbf{g_i'} \cdot \mathbf{a}_{t-1}$. I again focus on farmers who lie on or near the boundary characterised by corollary 1, and analyse how adoption decisions change when beliefs are changed following the observable behaviours of one's peers.

Model Implication 5 *Increases in beliefs stemming from increased adoption by peers can induce adoption regardless of learning costs. For any value of $\bar{e}(S_{it})$, an increase in the share of adopters induces adoption if $\frac{\partial p_{it}^k}{\partial(\mathbf{g_i'} \cdot \mathbf{a}_{t-1})} \Rightarrow \Delta P(T_i') = 1$.*

This implies that increases in the share of peer adopters increases farmer i's profitability beliefs, which induces adoption regardless of learning costs. This negates the possibility that a model implication parallel to implication 1 operates through the belief channel. This

[37] j need not have increased his/her beliefs in the profitability of the new crop during the period of adoption; he/she might have been induced to adopt because of a decrease to learning costs.

stems from the fact that it is not costly for farmers to update their beliefs relative to the process by which they acquire production knowledge. Adoption might ensue if beliefs are sufficiently high, even without the application of learning effort, due to the costless nature of belief-updating.

Model Implication 6 *Disadoption along the network decreases profitability beliefs and delays adoption regardless of learning costs. If under vectors* $\mathbf{D_{-i}}$ *and* $\mathbf{T_{-i}}$ *i would have adopted the new variety at* $t = T_i$*, for any* $\bar{e}(S_{it})$*, there are some values of* $\mu(q)$ *at which* $\frac{\partial p_{it}^k}{\partial(\mathbf{g_i'} \cdot \mathbf{d}_{t-1})} < 0 \Rightarrow \Delta P(D') = 1$*, and adoption would be delayed* ($t > T_i$)*.*

This is the mirror image of model implication 5. These two implications are depicted in figure 2.5 at each point A, B, and C. Increases in the share of adopters will always have the effect of pushing farmers above the boundary, and increases in the share of disadopters will have the opposite effect.

Model Implication 7 *If* $G_{ij}^{ST} = G_{ij}^{WT}$*, then under reasonable conditions, the adoption and disadoption of* ***WTs*** *induce stronger changes to beliefs than the adoption and disadoption of* ***STs*** *do.*

Conditions referred to in model implication 7 are discussed in appendix A.1.3. This result is initially surprising. There is a continuous association between STs' beliefs and own beliefs throughout decision-making. Since i observes his/her ST's transition to adoption, the direct effect of j's adoption or disadoption pertains to the difference between period $t-2$ and $t-1$ beliefs. For WT, without the ability to observe beliefs over time, change in j's actions signals a (probable) sequence of changes in j's beliefs. Thus, i reacts to WT actions as if responding to a whole sequence of changes in beliefs. This is the reason behind the greater magnitude in model implication 7.

Tests for Resource-Pooling

I test for the possibility of risk-sharing in family networks by suggesting that networks best able to *absorb* risk are more able to produce initial adopters of a new technology. However, since such networks prefer to minimise risk in their optimal investment portfolio, within-network adoption is limited.

Model Implication 8 *Adoption of the new crop by resource-pooling (family) ties decreases the probability of adoption, and the abundance of resource-pooling links and resources (land) increases the probability of adoption.*

2.2.5 A basic empirical approach

I am interested in the analysis of $\mathbf{T}$, a random variable that denotes the period of adoption of the new crop. Using notation described throughout, model implications require estimation of a function of the type:

$$Pr\{\mathbf{T}=t|T\geq t,\mathbf{G},\,\mathbf{G'},\,\mathbf{a_0}\ldots\mathbf{a_t},\,\mathbf{d_0}\ldots\mathbf{d_t},\,\mathbf{x_t}\}=$$

$$f(\underbrace{\mathbf{G'}\cdot\mathbf{a_{t-1}},\mathbf{G'}\cdot\mathbf{d_{t-1}}}_{\text{Direct Belief}},\overbrace{(\mathbf{G'})^{\mathbf{t-k}}\cdot\mathbf{a_{t-k}},(\mathbf{G'})^{\mathbf{t-k}}\cdot\mathbf{d_{t-k}}}^{\text{Indirect Belief}},\underbrace{\mathbf{G}\cdot(\mathbf{a_t}+\mathbf{d_t})}_{\text{Learning}},\overbrace{\mathbf{x_t}}^{\text{Individual}},\underbrace{\mathbf{G'}\cdot\mathbf{x_t},\alpha_t,\nu_G}_{\text{Contextual/Correlated}})\tag{2.12}$$

in which $\mathbf{G},\mathbf{G'}$ can be separated into three matrices that differentiate ST, WT, and pooling/family ties (FT); $(\mathbf{G'})^{\mathbf{t-k}}\cdot\mathbf{a_{t-k}}$ and $(\mathbf{G'})^{\mathbf{t-k}}\cdot\mathbf{d_{t-k}}$ represent indirect network effects of belief-updating for each period $t-k\leq t-2$ chosen by the researcher. There are similarities between this function and a traditional network model of peer effects, as Manski [1993] outlines. The belief and learning variables are similar to *endogenous peer effects*, described as individual behaviours that vary with the behaviours of a group. The differences in the current context are: first, information and incentives, and hence peer-induced behaviours, vary according to the source of social influence (i.e., ST, WT, or FT). Second, the history of peer group behaviours matters because adoption might be followed by disadoption. This relates to a third point; the peer effect is a function of a behaviour (disadoption) that is not the same as the dependent variable of interest in the model (i.e., time of adoption).

Analysis of contextual and correlated effects take a traditional approach. *Contextual effects* induce behaviours through exogenous characteristics of a peer group. This might occur if period zero beliefs correlate with peers' period zero beliefs. Without controlling for contextual effects, I might observe adoption by farmer j, followed by farmer i, and incorrectly conclude that j's behaviour induced i to adopt. However, contextual effects imply that similarities in initial characteristics played a larger role. I control for such individual characteristics in $\mathbf{x_t}$, and peer characteristics in $\mathbf{G'} \cdot \mathbf{x_t}$, to the extent that they are observable and measured by the researcher. *Correlated effects* relate to the environment in which farmers reside. Thus, network effects, ν_G and time effects, α_t, must be controlled for adequately since both induce adoption separately from endogenous peer behaviours and contextual factors.

I can control for correlated and contextual effects (to the extent possible) with network data, but contextual effects are less of a concern in the current analysis than what is described in Manski [1993] for three reasons. First, if exogenous characteristics lead i and j to adopt a new crop, i and j adopt at the same time, suggesting that $t-1$ (and earlier) variables do not explain adoption behaviours. It would suggest that j's disadoption does not affect i. Second, model implication 1 contributes to an interpretation of social influences that drive adoption. The implication implies that if i's beliefs suggest that the new crop is infeasible, peer experiences that decrease learning costs should have no effect on him/her, even if his/her exogenous characteristics are the same as j's. Thus, contextual effects are a concern only if model implication 1 is falsified. Finally, separating WT networks from ST networks allows me to uncover whether there are asymmetries in their effects that accord with the model. If asymmetries exist, and the intensity of belief (learning) effects increases with the adoption or disadoption of WTs (STs), I am convinced of a socially induced effect.

2.3 Empirical Context and Data

The empirical context required to analyse the implications of the model in the previous section is one in which there is adoption and disadoption of a new crop variety (or technology), accompanied by a distinct process of learning during which farmers seek production knowledge tied to a production process. Given strong evidence in Conley and Udry [2010a], which demonstrates pineapple farmers' acquisition of production knowledge (in the optimal application of fertiliser) from the experiences of peers, the second of these two conditions is satisfied, and pineapple cultivation in Ghana during the 1990s is a promising system of study. Further investigation shows that pineapple adoption was accompanied by disadoption, even during early stages of pineapple cultivation in communities. Due to the easily observable nature of pineapple cultivation and the presence of sunk costs in pineapple adoption, pineapples are planted 10 to 20 months before they can be harvested [Harou et al., 2017]. The initial decision to adopt pineapple, and the decision to disadopt, is consequential and likely to be noticed by many [Besley and Case, 1993, Chavas, 1994]. These two contextual characteristics render pineapple cultivation in Ghana an ideal setting to analyse predictions in the model. With the appropriate network data, I can test whether social-updating of profitability beliefs plays a role in pineapple adoption decisions relative to social learning regarding production knowledge.

Data came from two household surveys that form a panel; one was conducted from

1996–1998, with multiple waves of data, and the second during 2009, with the same set of households in four communities in Akwapim South district in Ghana.[38] This study combines a rich social network module with timing of pineapple adoption and disadoption, and individual characteristics, to construct pseudo-panel data to be used during time-to-event analysis. All modules are designed to create time variation in variables of interest (inclusive of the social network survey), allowing me to construct dynamic social network variables that correspond to measures suggested in section 2.2.5.

The initial sample collected during the 1990s was selected randomly, and intended to include 60 households in each of the four villages (207 households). The 2009 sample included the same 207 households in a panel, and found the representatives of roughly 84% of the original households that consented to participate in the initial survey. These households were supplemented by additional households in 2009, stratified by age of household head since most of the households dropped due to attrition of the older heads of household.

The 2009 sample includes 77 and 89 households in each of the four village, 70 of which were dual-headed. Surveys were administered to the household heads and spouses (15 male household heads had two wives, both of whom were interviewed), resulting in a sample of 631 individuals. Of these, 508 provided information on historic pineapple cultivation, and the remainder did not control any plots of land in the 2009 data. Non-responses in a subset of additional questions reduced the sample to 482 individuals in the main empirical specifications. Technical details and descriptions of the sampling, survey, and tests conducted in the field are provided in Walker [2011].

[38] Data were collected by a team led by Chris Barrett and Thomas Walker in collaboration with ISSER during 2009. These same communities were studied by Conley and Udry [2010a] through household survey data collected in 1996, 1997, and 1998. The data are available to download at `http://barrett.dyson.cornell.edu/research/datasets/ghana.html` and `http://www.econ.yale.edu/~cru2/ghanadata.html`, respectively.

The remainder of this section discusses data used during analysis. It describes the data used to measure the timing of pineapple adoption and disadoption. It then discusses the nature of the social network module and how it can be used to construct time-varying measures of network adoption and disadoption decisions (both shares and totals). It concludes by discussing control variables used during analysis.

2.3.1 Pineapple Adoption and Disadoption

To account for variation in the timing of pineapple adoption, I use a retrospective question on the 2009 survey. The question asks farmers to recall the month and year during which they started and ended pineapple farming, conditional on having ever farmed the product.[39] Figure 2.6 shows that pineapple farming was increasing steadily during the early 1990s, but a number of farmers had already adopted pineapples on their farms only to disadopt later, even during very early stages of pineapple farming. By 1990, 7.8% (38) of farmers had adopted pineapple in the four villages, and nearly one-fifth of them (7) had disadopted. By 2000, 24% (121) of farmers had adopted pineapple, with 3% (19) disadopters. By 2004, the number of disadopters had doubled, and the growth rate of pineapple adoption reached its peak; 22 farmers alone entered pineapple farming during 2003.

Figure 2.7 shows that prices of the variety of pineapple grown in Ghana, smooth cayenne, dropped steeply during 2004 due to a shift toward MD2 variety among consumers in Europe [Fold and Gough, 2008]. After this point, the number of pineapple adopters declined slowly while the number of disadopters increased; there were more disadopters during each year after 2004 in the sample than there were adopters. This exogenous shock to pineapple prices

[39] I aggregate adoption decisions by year. The initial year of pineapple cultivation reported in focus groups in 2017 was the same as that reported in 2009.

is valuable when testing model implication 1. Farmers' profitability beliefs are likely to be lower following this shock than prior to it, allowing me to test whether learning effects are conditional on high profitability. Throughout analyses, survey responses to this question help construct T and D, the timing of pineapple adoption and disadoption decisions, respectively. This information helps construct vectors $\mathbf{a_t}$ and $\mathbf{d_t}$, the vectors of adoption and disadoption decisions in each village, which are multiplied by the adjacency matrices of the village social networks described in the following section.

2.3.2 Network Data

The social network module, fielded at the beginning of the 2009 wave of surveys, maps the entire in-sample social network in each of the four study villages, and includes detailed questions regarding relationships among all respondents in each village. Each was asked whether they know other sampled individuals (in random order) in the network module. If they responded yes, they were asked further questions that elicited the nature of the relationship. I construct directed networks (i to j) using measures of friendship ties from the following question in the social network module: "Would you consider this person to be (not a friend, acquaintance, distant friend, good friend, close friend)?" I categorise links according to **ST** and **WT**. STs are either "good friends" or "close friends," and WTs are either "acquaintances" or "distant friends." For example, $g_{ij}^{ST} = 1$ if i indicates an ST link with j, and zero otherwise.[40]

Due to a potential confound of resource pooling, I also separate ties according to kinship relationships. In this region of Ghana, there is a strong social norm of resource-sharing among

[40]Similarly, $g_{ij}^{ST\prime} = \frac{1}{\sum_{j \neq i} g_{ij}^{ST}}$.

family ties, reflected in the data (over 90% of family ties and only 20% of friendship ties engage in mutual gift-giving). I construct categories according to responses to the question "How is this person related to you?" Responses are placed in three mutually exclusive categories according to whether the individual referred to a direct family member (e.g., spouse, child, step-child, parent, grandparent, grandchild, or sibling), an extended family member (e.g., uncle/aunt, niece/nephew, cousin, or "other relative"), or a village friend.[41]

Five hundred seventy individuals (of 631) participated in the networks module—155 (162) from village 1, 148 (154) from village 2, 129 (150) from village 3, and 138 (165) from village 4. In theory, this should result in the observation of 89,304 direct links across the four villages[42]. However, a small number of participants were unable to complete the survey, resulting in 86,880 observations of links. Of these, 1,284 were dropped because a respondent incorrectly stated that the linked-to individual lives "outside of the village" (1,232 cases) or the link was not a permanent resident of the village (e.g., priest or extension worker). Thus, 85,596 observations of directed links were available for analysis. 31,550 links, or 36.9% of linked-to individuals, were unknown to the survey respondent.[43] The resulting social network variables are built using the remaining 54,046 observations on links.

Tables 2.1 and 2.2 show the distribution of relevant link measures by village. Residents in village 4 have more family members (both direct and extended) than the other villages have. Villages 2 and 3 appear more talkative; residents in these villages have daily conversations with more than 60% of the people they know (fewer than 50% in the other two villages). Residents in villages 1 and 4 have the longest standing relationships with people they know,

[41] In addition to the two questions described above, questions in the module also asked "How long have you known this person?," "How often do you speak to this person?," and "Have you ever given (received) a gift to (from) this person?" Each question had codes associated with responses, which I list in summary tables.

[42] Calculated according to $\sum_{v=1}^{4}(n_v)(n_v-1)$, where n_v represents the number of participants in the network module in village v, and n_v the number of people sampled in village v.

[43] Vanderpuye-Orgle and Barrett [2009] find similar patterns in a 1996–1998 data set in the same context.

with over 70% reporting that they have known their links for over 10 years. There is far less inter-village heterogeneity in the percentage of links reported as STs or WTs (Table 2.2); nearly 40% of all possible links are reported as WTs, and 15% as STs.

Table 2.3 divides responses according to how they are used during analysis. First, the majority of individuals listed as being direct family or extended family in the first two columns are also reported as being STs. This is unsurprising, though it suggests the importance of separating family relationships from friendships when accounting for the effect of STs during learning. The third column separates weak from strong friendship ties, and shows that about 16% of all links with non-family members are categorised as STs, in comparison to 62.5% for WTs. I separate the overall network into four mutually exclusive categories of links—direct family (DF), extended family (EF), strong friendship ties (ST), weak friendship ties (WT)—during analysis. Their respective adjacency matrices are denoted $\mathbf{G_{DF}}$, $\mathbf{G_{EF}}$, $\mathbf{G_{ST}}$, and $\mathbf{G_{WT}}$, in which each cell $G_{ij,k}$ is equal to one when i lists j as a relation of type k (in DF, EF, ST, WT), and zero otherwise.

The adjacency matrices, along with vectors $\mathbf{a_t}$ and $\mathbf{d_t}$, are sufficient to create network-related variables required for analysis, but it is possible that friendships recorded in 2009 did not exist for the entirety of the time horizon analysed in the study. I address this by creating time-varying adjacency matrices using information on the length of the relationship reported by i for each link ij. I assume the most conservative approach for the primary empirical specification, and compare analyses of the time-varying matrices with matrices that I do not vary over time, finding no qualitative differences (with stronger quantitative effects when I do not vary matrices over time).[44]

[44]For time-varying matrices, I assume that answers listing "10+ years" or "All my life" are individuals that person i has known for the entirety of the study period. Answers listed as "5–10 years," "1–5 years," and "<1 year" are relationships of length 10, 5, and 1 year, respectively. This allows me to add a time subscript to each adjacency matrix. A final restriction is that individual j enters the network measure only if he/she is 18 years old at time t. For example, if an individual i has known j for only "5–10" years, the

Two final concerns relate to whether relationship types changed over the course of the study period. This is only a problem in the articulation of ST and WT, since direct family ties do not change with much frequency over time. With ST and WT, the primary source of concern derives from the possibility that pineapple farming was instrumental in the establishment of a ST. This might be the case if two farmers became close friends while they were both farming pineapple. Data were collected during 2009, a year during which many farmers had already disadopted pineapple. If pineapple farming was instrumental to a friendship, one might use similar logic to suggest that after disadopting, farmers no longer categorised pineapple-based friendships as ST. Thus, the 2009 categorization of relationships captures more permanent aspects of friendship. A more likely alternative is that some friendships were strengthened due to mutual pineapple adoption, and remained strong following disadoption. The discussion of appendix tables A2 and A3 provides convincing evidence that this concern does not appear relevant in this context. The second concern is that the categorization of j as an ST or WT need not be time-constant. The data unfortunately are unable to express such endogenous switching of tie-type. Nevertheless, the appendix discussion of table A2 suggests that selection of ST correlates most strongly with permanent individual characteristics, such as sex, age, and years of education, which suggests endogenous switching is less of a concern.

2.3.3 Control Variables

Control variables are either time-invariant or time-varying. Variables in the former category include gender, highest school level attained, measures of human capital obtained through responses to English comprehension and arithmetic tests, binary measures of whether a

relationship is assumed to have existed only since 1999 in the time-subscripted matrix $\mathbf{G_{k,t}}$. Thus, the new network adjacency matrices are sub-scripted by time t, and can evolve.

farmer was trained to farm pineapple by a business entity, government extension worker, or NGO extension worker, a measure of subjective risk preferences, a binary variable indicating whether an individual has ever controlled land during years prior to and including 2009, and a measure of farming land quality.[45] Variables in the latter category include age and area of land owned at time t.

Table 2.4 shows summary statistics associated with each of the time-constant measures. Forty-eight percent of the sample is female, with the highest share of females residing in village 3 (54%). Participants completed, on average, between three and four years of education. Scores associated with the human capital measure are in the range of 0–8, based on correct responses to tests administered by the enumerators. Average scores in English comprehension are generally lower than math scores. The lowest scores associated with these measures were recorded in villages 3 and 4. The overall correlation between math and English scores is 0.49, math and years of schooling is 0.29, and English and years of schooling is 0.19. Thus, it appears that the three measures of human capital describe disparate abilities.

Following Binswanger [1980], subjective risk preferences were collected using a survey method that elicited certainty equivalents associated with losses.[46] Higher scores indicate greater risk-aversion, since the respondent preferred an increasingly costly stable loss to a risky loss in these cases. Individuals in villages 2 and 3 had higher average levels associated with this measure, suggesting they are more risk-averse.

On the survey, after farmers stated whether they have ever farmed pineapple, they were

[45]The particular moment of pineapple training is certainly time-varying, but the data do not allow me to date the training.

[46]Each respondent received a score from 1–11 based on sequential binary choices of loss outcomes associated with use of agricultural technology, in which one alternative has zero loss variance and the second has a non-zero variance. The initial choice presented a middle option, and the question was iterated sequentially based on the farmerâĂŹs acceptance (rejection) of this outcome by increasing (decreasing) the variance associated with the second outcome until the respondent chose the stable (risky) technology.

asked whether they had ever received pineapple training. If they answered yes, they were prompted to discuss the relationship they had with the trainer. A binary measure is created that indicates whether the trainer was a business relation, an extension worker, or an NGO worker. Other possibilities included village-based friendship relationships, which are not included here since the effects of these relationships are captured using the network measure discussed above. Villages 2 and 3 were the only villages with exposure to training through business relationships; 18% of farmers in village 3 and 8% in village 2 were trained by such relations. These same villages were also exposed to pineapple training provided by NGOs. Each village had access to governmental extension workers who trained farmers in pineapple cultivation. Farmers were also asked whether they "own or currently control any plots of land in or near this village, including fallow land." A binary variable was created that indicates whether the farmer answered yes or no to the question. Approximately 40% of respondents reported that they did not control plots of land during 2009.

There are detailed data on farmland attributes collected with the help of GPS tools used to measure geographical coordinates and altitudes of farmers' plots. Several point measures were taken on each plot, proportional to the land size of the plot being measured. In this way, objective measures of both land size and altitude were obtained. I take advantage of the altitude measurements on each plot to construct absolute measures of the degree of land slope. Each point measure reports the total meters above sea level for a geographical coordinate. Thus, the plot-level standard deviation of the altitude measures provides an objective measure of this slope. In cases in which farmers own multiple plots, cross-plot averages of the measure are used to control for land quality. Outcomes associated with these measures suggest that there is more intra-village variation than inter-village variation regarding slope. Village 1 has the highest average measures associated with curvature, but also the highest variance. The sample coefficient of variation for the remaining three villages is in the range of 0.5–0.7, which suggests that the slope conditions of these villages are similar.

The areas of each farmers' plots were objectively measured by calculating the square meters associated with each plot from the geographic coordinates of plot borders. Each plot was then connected to a survey module that asked farmers to state which plots they control, how they came to own the plots, and when (month and year). Thus, the area owned at time t can be calculated using $x_{ipt} = Area_{ip} \times Owned_{ipt}$ for individual i, plot p, at time t. The total area of land owned at time t can be calculated by summing this value over the total number of plots owned by individual i at time t: $x_{it} = \sum_{p=1}^{P} x_{ipt}$.

Table 2.5 shows summary statistics by selected years of the time-varying outcomes age and area of land owned at time t. The number of people included during analyses increases from year to year. The majority of the sample (332 individuals) was 18 years or older by 1990, before the peak of the pineapple adoption era during the mid-1990s to mid-2000s. Of the 130 people who reported that they own the land they control in 2009, 43 (33%) had owned some land by 1990, and 81 (62.3%) by 2000. The share of land owners does not vary significantly across villages. However, the amount of land owned most years is higher in villages 1 and 2 than in villages 3 and 4.

2.4 Estimation Strategy

To examine the network effects of social learning on pineapple adoption, I analyse the timing of pineapple adoption among smallholder farmers in Ghana. Not every farmer adopted pineapple during the time of the study, so a model that incorporates observation censoring is used. The estimation strategy uses a time-to-event, or hazard, model to estimate the effects of farmer characteristics, including adoption decisions in a farmer's network, on the timing of farmer entry into pineapple cultivation. Following Allison [1982], I employ a discrete-time method to analyse these histories, given constraints imposed by available data and analytical flexibility of discrete-time models with respect to time-varying covariates and the effects of time itself[47].

There is a sample of n independent individuals ($i = 1, \cdots, n$), and each individual becomes at-risk of adopting pineapple at $t = 1$. Each can become at-risk once he/she is in a position to decide whether to farm pineapple. Thus, I assume that $t = 1$ in 1969, the first year in which anyone adopted pineapple farming in the data. However, if the farmer is not yet 18 years old by 1969, he/she does not contribute to estimation of the hazard rate until 18.[48] An observation is collected for each point until time T_i. This is the year of pineapple adoption for individual i. If a farmer is yet to adopt pineapple at the endpoint of the data-collection period in 2009, the observation is censored. Given T, a random variable denoting the uncensored time of pineapple adoption, and $\mathbf{z_{it}}$, a $K \times 1$ vector of explanatory variables that can take on different values at different discrete times, a discrete-time hazard rate is provided by:

$$P_{it} = \Pr\left[T_i = t | T_i \geq t,\, age_i \geq 18,\, \mathbf{z_{it}}\right]. \tag{2.13}$$

This equation is similar to equation 2.12, which I estimate to test model implications. Since some observations are censored, I rewrite equation 2.13 to represent the likelihood of the data-generating process. I let δ_i be 1 if the observation is uncensored (i.e., I observe

[47]There are over 200 incidences of entry into pineapple farming over a 40 year time-horizon observed in the data. In such discrete-time models, each time interval must contain a sufficient number of events for calculations to converge. Discrete-time models allow use of time-varying covariates, and do not impose restrictions on a functional form for time effects relative to continuous time proportional hazard models, for example. For a more detailed discussion, see Allison [1982].

[48]Eight farmers in the data adopted pineapple prior to turning 18. I impose that these farmers enter the model one year prior to their decision to adopt (e.g., a 17-year-old pineapple adopter enters the model the year in which he/she is 16 years old).

pineapple adoption before 2009), and zero if censored. The likelihood function is written as:

$$L = \prod_{i=1}^{n} \left[\Pr(T_i = t | age_i \geq 18,\, \mathbf{z_{it}})\right]^{\delta_i} \left[\Pr(T_i > t | age_i \geq 18,\, \mathbf{z_{it}})\right]^{1-\delta_i}, \tag{2.14}$$

which states that each uncensored individual contributes a factor toward the density function for T if T_i is observed. Censored individuals contribute to the likelihood that T_i occurs after 2009. When periods are discrete, the term can be simplified and written as a log-likelihood:

$$\log L = \sum_{i=1}^{n} \sum_{j=1}^{T_i} y_{it} \log\{P_{ij}/(1 - P_{ij})\} + \sum_{i=1}^{n} \sum_{j=1}^{T_i} \log(1 - P_{ij}) \tag{2.15}$$

in which y_{it} is equal to 1 if person i adopts pineapple at time t, and zero otherwise.[49] The first summation on the right side contributes P_{it} to the calculation of the log-likelihood for periods during which pineapple adoption by individual i is evident, and subtracts their log-probability of not adopting pineapple during this period $(1-P_{it})$ from the second summation on the right side. If an individual's adoption decision is censored, he/she contributes only to the log-likelihood calculation in the second summation on the right side.

In practice, the maximization problem associated with this simplification transforms the analysis to a simple binary dependent variable estimation procedure when the data are inputted appropriately. When a left-hand-side variable, y_{it}, is equal to one if $T_i = t$ and zero if $T_i \leq t$, estimation of y_{it} maximises the likelihood of the equations above. Thus, I treat each discrete time unit for individual i as a separate observation. During period T_i, in which farmer i decides to adopt pineapple, farmer i contributes to the calculation of parameters associated with P_{it}. During all other periods prior to T_i, he/she contributes to the calculation of $(1 - P_{it})$. A censored observation contributes information only to the second term of the RHS in equation 2.15.

Consequently, P_{it} can be specified using any dichotomous choice estimator, such as probit, logit, or linear probability model (LPM). To ease interpretation of empirical tests, I use LPM

[49]See appendix section A.1.6 for the steps required for this simplification.

to estimate variants of equation 2.12. I begin by considering estimation of P_{itv} using

$$P_{itv} = Pr\{T_i = t | T_i \geq t, \mathbf{g_{ikt}},\ \mathbf{g'_{ikt}},\ \mathbf{a^a_t},\ \mathbf{d_t},\ \mathbf{x_{it}}\} =$$

$$\overbrace{\gamma^a_{ST}\mathbf{g'_{ST,it}} \cdot \mathbf{a_{t-1}} + \gamma^d_{ST}\mathbf{g'_{ST,it}} \cdot \mathbf{d_{t-1}} + \gamma^a_{WT}\mathbf{g'_{WT,it}} \cdot \mathbf{a_{t-1}} + \gamma^d_{WT}\mathbf{g'_{WT,it}} \cdot \mathbf{d_{t-1}}}^{\text{ﬂ}\rightarrow\text{Belief-Updating}}$$

$$\overbrace{+\rho_{ST}S^{ST}_{it} + \rho_{WT}S^{WT}_{it} + \rho_{ST,I}S^{ST}_{it} \times I + \rho_{WT,I}S^{ST}_{it} \times I}^{\text{æ}\rightarrow\text{Social Learning}}$$

$$\overbrace{+\phi_{DF}\mathbf{g_{DF,it}} \cdot - + \phi_{EF}\mathbf{g_{EF,it}} \cdot -}^{\text{Œ}\rightarrow\text{Resource-Pooling}}$$

$$+\beta\mathbf{x_{it}} \overbrace{+\delta_{ST}\mathbf{g'_{ST,it}} \cdot \mathbf{X_t} + \delta_{WT}\mathbf{g'_{WT,it}} \cdot \mathbf{X_t} + \delta_{DF}\mathbf{g'_{DF,it}} \cdot \mathbf{X_t} + \delta_{EF}\mathbf{g'_{EF,it}} \cdot \mathbf{X_t} + \alpha_t + \nu_v}^{\text{Contextual and Correlated Effects}} + \epsilon_{it} \tag{2.16}$$

which is the individual-specific and linearized analogue of equation 2.12, with inclusion of time-indexed, individual-specific networks, $\mathbf{g_{k,it}}$ (row-normalized vector $\mathbf{g_{k,it}}'$), for each type of link ($k \in ST$, WT, DF, EF). The row labelled Belief-Updating includes the average share of adopters and disadopters in the set of first-degree, weak and ST links for each individual at time $t-1$. The row labelled Social Learning includes measures of the sum of individuals with pineapple farming experience at time t.[50] Interaction term I is included as a means of testing model implications 1 and 4, and thus specific measures of I depend on whether I interact the learning effect by, respectively, a measure of beliefs in the feasibility of the new crop or a measure of learning capabilities. The row labelled Resource Pooling sums the number of direct family members and extended family members. ($-$ represents the unit vector that is of the same dimension as $\mathbf{g_{DF,it}}$ or $\mathbf{g_{EF,it}}$) who are heads of households in the village to explore model implications 8. I include individual characteristics, $\mathbf{x_{it}}$, and average network characteristics to control for contextual effects. Hazard models typically impose parametric assumptions on time-related trends. However, due to the ability to construct pseudo-panel data from the information collected on the survey, I am able to include time-fixed effects to non-parametrically account for time trends during each year through α_t. ν_v

[50] From section 2.2, $S^k_{it} = \mathbf{g_{k,it}} \cdot (\mathbf{a_t} + \mathbf{d_t})$

represents a village fixed-effect. In combination, α_t and ν_v control for correlated effects of pineapple adoption (i.e., environmental conditions such as price and network characteristics that lead farmers to adopt the new crop).

2.4.1 Tests of Estimated Coefficients

The specification above allows me to test each model implication discussed in section 2.2.4 and summarised in table 2.6 directly. Model implications 1 through 4 can be tested by examining whether coefficients $\boldsymbol{\rho} = \{\rho_{ST}, \rho_{WT}, \rho_{ST,I}, \rho_{WT,I}\}$ differ from zero. Model implications 1 and 4 require discussion of interaction term I, so I discuss them in further detail. Implication 1 requires that I interact S_{it}^k with a term that indicates belief in the infeasibility of adoption with learning. There are two approaches I can take. First, individuals with a high share of disadopters in their ST or WT networks might have lower beliefs in the profitability of the new crop, suggesting they are less likely to exert learning effort to increasing their knowledge of its production process. I prefer the second approach. Due to a drop in pineapple prices during 2004, I do not expect learning effort to change the probability of adoption relative to adoption decisions before 2004. Thus, for model implication 1, $I = \mathbb{1}(t > 2004)$ is a dummy variable that takes a value of 1 if the observation is entered into the likelihood maximization after 2004.

Model implication 4 requires that I interact S_{it}^k with a measure of learning capability. Unique to this dataset is an individual-specific measure of mathematical ability, $I = Q_i$, which proxies the analytical ability with which each individual has been endowed or developed through schooling. Using insights from Niehaus [2011], I assume that these numeracy skills are a complementary unit of knowledge that assist farmers to more accurately infer amounts of fertiliser, pesticides, labour, etc. from the experience of peers. Thus, $\rho_{k,I}$

amplifies the effect of ρ_k when $I = Q_i$.

I consider model implications 5 through 7, which can be tested by examining whether coefficients $\boldsymbol{\gamma} = \{\gamma^a_{ST}, \gamma^d_{ST}, \gamma^a_{WT}, \gamma^d_{WT}\}$ differ from zero and relate to one another. Of particular note is model implication 7, which states that direct effects that stem from increases in the share of adoption or disadoption among WTs induce larger changes in the probability of own adoption than similar increases among STs do. Regarding model implication 8, I expect increases in the number of family members present in the village, regardless of adoption status, to induce higher probabilities of adoption (i.e., $\phi_D F$ and $\phi_E F$ are greater than zero).

2.5 Results

2.5.1 How Do Peers Influence Beliefs?

Table 2.7 displays estimates of coefficients $\boldsymbol{\gamma}$, which can be analysed to test model implications 5 through 7. The first three columns estimate equation 2.16, without contextual (exogenous) peer effects, and the latter three estimate the same equation inclusive of these effects. In these three columns, interaction I is either not included or included in the first and second columns, respectively. The third column includes indirect effects of ST network behaviour, as model equation 2.8 suggests and section 2.2.3 discusses.

There is little difference in the magnitude of the listed coefficients based on the exclusion or inclusion of exogenous peer effects. Exogenous peer characteristics confound interpretation of the $\boldsymbol{\gamma}$ coefficients because the characteristics of the peer group might induce adoption separately from peer behaviours. This suggests that coefficients $\boldsymbol{\gamma}$ are unlikely to be biased by observable peer characteristics.[51]

Model implication 5 suggests that rising shares of peer adopters increase profitability beliefs, which consequently increase the probability of adoption. Both γ^a_{ST} and γ^a_{WT} are positive across all specifications, but only the latter is consistently statistically significant.[52] A 10% increase in WT adoption corresponds to a 0.5% increase in the linear probability of adoption during each year.[53] This is consistent with the first part of model implication 7, which suggests that beliefs change more drastically from changes in observable WT actions relative to ST behaviour. Since ST are likely to be communicating with each other with more frequency, changes to the adoption or disadoption status of ST are not as shocking as similar decisions made by WT. Controlling for such communication through the indirect effect of ST networks (insignificantly) increase γ^a_{ST}. Thus, I cannot reject the null hypothesis that increases in the share of WT adopters correspond to higher probability of adoption than increases in the share of ST adopters (see $H_0 : \gamma^a_{WT} \leq \gamma^a_{ST}$ in table 2.7).

Disadopter effects, however, demonstrate a different finding that accords with model implications 6 and 7. The marginal effect of an increase in the share of disadopters is negative and significant for WT, and not significantly different from zero for ST.[54] These results suggest that the observable decision made by WT to disadopt pineapple sends a strong signal to a prospective farmer, causing him/her to delay own adoption until the crop is deemed more profitable. It is surprising that ST disadoption does not correspond to a

[51] Changes in beliefs are a function of peer behaviour during period $t-1$, and thus the variables in front of $\boldsymbol{\gamma}$ include a one-period lag. A significant effect on the lagged term suggests that peer behaviour, not exogenous peer characteristics, influence adoption; if farmers adopt based on similarities in exogenous characteristics, adoption should occur simultaneously, nullifying the effect of time lags.

[52] The former is statistically significant only when the model is fully specified (last column of table 2.7), when I control for the indirect effects of ST networks.

[53] When there is a 10% increase in WT tie adoption, over the course of the next 10 years, the probability of non-adoption decreases by $1-(1-.005)^5 = 0.05$, or 5%.

[54] A 10% increase in WT disadopters decreases the probability of adoption by roughly 0.1% in any year. Over ten years, the peer influence of these WT disadopters increases the probability of non-adoption by 10%.

decrease in the probability of adoption. Disadoption can be a function of many factors, some of which are unrelated to the general profitability of the new crop (e.g., preference, soil incompatibility, etc.) because ST can communicate reasons for disadoption, and the signal a farmer receives from these reasons might not necessarily decrease expected profitability of the new crop.

Turning to model implication 7, I find that the null hypothesis is rejected in the context of WT disadoption. Increases in the share of WT disadopters decreases the probability of adoption to a much greater extent than similar increases in the share of ST disadopters. The model suggests that one updates beliefs based on observable WT behaviour by decreasing the probability of the high profitability state for pineapples. A change from adopter to disadopter status by a WT shifts beliefs by $|G_{ij}\mathbb{E}[\bar{\mathbf{q}}_{\mathbf{D}}] - G_{ij}\mathbb{E}[\bar{\mathbf{q}}_{\mathbf{A}}]|$, which is much larger (in absolute magnitude) than $G_{ij}\mathbb{E}[\bar{\mathbf{q}}_{\mathbf{A}}] - G_{ij}\mathbb{E}[\bar{\mathbf{q}}_{\mathbf{N}}]$. This is consistent with the effects shown in table 2.7; γ^d_{WT} is double in size (in absolute terms) relative to γ^a_{WT}. Disadoption by WT shifts beliefs much more drastically than adoption.

2.5.2 Can Peer Experience Reduce the Cost of Learning?

Estimates of ρ_{ST} and ρ_{WT} provide tests of model implications 2. Table 2.8 is structured similarly to table 2.7, showing a positive and significant effect for ρ_{ST} across all specifications, and a very small positive but insignificant effect for ρ_{WT}.[55] The model predicts that communication is less costly among ST than WT, and thus the cost of learning from ST should be less than that from WT. This means that STs who adopt the new crop increase the probability of adoption more than WT, as model implication 3 suggests. Null hypothesis

[55]Five additional STs who adopted the new crop increase the probability of adoption by 1.5% during any year.

$H_0 : \rho_{ST} \leq \rho_{WT}$ is consistently rejected at a high confidence level, corroborating the model implication.

The time lag associated with the profitability belief variables in table 2.7 suggests that contextual effects play a minor role in biasing coefficient estimates of $\boldsymbol{\gamma}$, but the same cannot be said about learning variables $\mathbf{g_{k,it}} \cdot S^k_{it}$; one learns from experienced, contemporaneous farmers. Thus, model implications 1 and 4 derive further insights into whether the effect is measuring the effect of social learning or peer characteristics. Model implication 1 suggests that adoption by ST only influences the probability of adoption positively if a farmer has reason to believe that the new crop is more profitable than the status quo is. The shock to sweet cayenne pineapple prices in 2004 allows me to test whether experienced ST (or WT) have the same effect on the probability of adoption before or after this period. Thus, I allow I to interact years including and after 2004 with the number of experienced pineapple farmers. I do not expect farmers to apply learning effort when the crop is not profitable (i.e., after 2004). Thus, the linear combination $\rho_{ST} + \rho_{ST,I}$ should not be statistically significantly different from zero. As the null hypothesis on this test indicates, I cannot reject a null that these two coefficients sum to zero. Point estimates are identical in absolute magnitude: 0.003 before 2004 and -0.003 after 2003.[56].

To provide further evidence of multi-object learning, I conduct a placebo test to assess whether the 2004 market shock changes the nature of the updating process associated with profitability beliefs in a manner analogous to how the shock might change the effect of learning effort. The market shock (placebo treatment) should not influence how farmers update profitability beliefs from peers, which implies a null interaction effect. Appendix

[56]Sensitivity analysis shows that this effect is sharp around 2004. If the post period is defined by $t > 2002$ or $t > 2006$, the effect is less pronounced. This is expected since years in which learning is still theoretically taking place (2003 and 2004) would be incorrect in the former case, and unprofitable years (2004 and 2005) would be binned into the wrong side of the interaction in the latter case, biasing results.

table A5 presents results of the test. Unlike coefficient $\rho_{ST,I}$ in table 2.8, null hypotheses for $\boldsymbol{\gamma}$ cannot be rejected.

2.5.3 Cost of Learning and Mathematical Ability

If peer farming experiences learning costs, model implication 4 suggests that learning costs should decrease further for farmers who developed, or are endowed with, higher learning capabilities. The measure of numeracy discussed in section 2.3 proxies learning capabilities, Q_i. Model implication 4 suggests that high-performing farmers learn more from ST than low performing farmers do. This requires interacting Q_i with S_{it}^k. I test whether ρ_k increases when the peer network includes only peers who scored 80% or above on the math test (i.e., peers with high learning capabilities), S_{it}^{k***}. Table 2.9 shows results from these specifications, which shows that learning effects are present only among those who have high scores on the math test. Figure 2.9 demonstrates this effect, especially with respect to the ST effect. ρ_{ST} increases across specifications in the figure, suggesting that as learning capabilities increase in a peer group (and a farmer), the ST effect on adoption increases. This strongly suggests that farmers acquire production knowledge from the experiences of STs; farmers with higher learning capabilities are better able to take advantage of ST farming experience.

2.5.4 Model Implication 8: Resource Pooling

When there is risk-sharing or resource-pooling in direct family (DF) networks, the learning effect might not operate the same way as learning among friends does. Column 1 in 2.10 includes family network variables in the same manner as ST and WT do by analysing coefficients γ_{DF}^a, γ_{DF}^d, ρ_{DF}, and $\rho_{DF,I}$. There is a divergent pattern relative to ST and WT networks; when the share of DF adopters increases, one's own probability of adoption decreases. It is unlikely that family adoption decreases own profitability beliefs. Rather, if there is risk-sharing in the family network, one family members' pineapple adoption might be hedged by the decision not to adopt by other family members.

As the number of experienced DF increases, the probability of adoption increases. Since there is reason to test whether this is more correlated with the total number of DF than experienced DF, I include total number of DF residing in the village (as village heads) in column 2. The coefficient for S_{it}^{DF} attenuates and is no longer statistically significant.[57] In column 3, I omit S_{it}^{DF} from the analysis and analyse the effect of the number of family ties. As predicted by a risk-sharing hypothesis, the number of family members is positive and statistically significant.

Model implication 8 ties analysis of the adoption decision to the availability of land on which the family can plant the new crop. Thus, the total land owned by a family is included in column 4. It is a more significant predictor of adoption than the number of family members residing in the village. Column 5 shows a horse-race regression among all covariates included thus far, suggesting that the most significant predictors of pineapple adoption stemming from the effect of DF networks are the pineapple disadoption behaviours of DF and the land size of the DF in the village. DF disadoption is a consistently negative and significant predictor of own adoption across all specifications in table 2.10. This is likely due to the characteristics of earlier adopters in the family network.

One possibility suggested to me by residents of these villages is that early within-family adopters are wealthier than other family members, and have more responsibility to share

[57]This is not the case if a similar approach is applied to analyses of ST and WT. In these cases, ρ_{ST} and ρ_{WT} increase in magnitude and are statistically significant in a larger confidence interval than when $N_{ST,it}$ or $N_{WT,it}$ are not included in the specification.

resources with kin.[58] I include a final regressor in column 6, own land size minus average land size of one's DF network, which ranks within-village, within-family land size to proxy wealth. The coefficient is positive and statistically significant at the 99% confidence interval, which suggests that the conjecture is possible.

Family members' adoption and disadoption decisions cannot be interpreted through the lens of belief-updating or decreases in learning costs. It is likely that learning and belief-updating occur among family ties, but the two are difficult to disentangle with analysis. Peers influence each others' adoption decisions not through learning channels alone. Future research should explore whether resource-pooling depends on the type of network effects being analysed.

2.6 Discussion: Re-interpreting Other Findings

The social learning model presented in this paper suggests that network-based targeting policies should be implemented cautiously if disadoption is a likely outcome. I elaborate on this point briefly by discussing how this model reinterprets conclusions from BenYishay and Mobarak [2014] and Beaman et al. [2015], two recent studies that have increased diffusion rates of agricultural technologies through policies using social network theories of technology diffusion. In Beaman et al. [2015], the researchers collected a social network census prior to conducting an experiment during which they injected a new technology into the most central (theoretically optimal) network node, and compared diffusion outcomes to a benchmark treatment in which the injected node was selected by village leaders based on

[58]Social norms regarding land inheritance are strong in Ghana. In the Akwapim region, land is inherited through matrilineal heritage, so family members endowed with more land are more likely to have acquired it through inheritance than by purchasing it. Nevertheless, land is often bequeathed to offspring strategically, which influences asset accumulation decisions across generations [Ferrara, 2007]. For discussions concerning land rights in Ghana, see Goldstein and Udry [2008].

the local knowledge of progressive farmers. The network that constructed the theoretically optimal injection point was a network of farmers with whom the sampled farmers discussed agriculture practices.

My discussion relies on an assumption that this network is more similar to a network of ST than WT, since communication costs are likely lower among these links. It is more likely to be a network of individuals who share production knowledge than a network that shares profitability beliefs alone. There was no diffusion of the new technology in 45% of the benchmark villages three years after initial injection, and a 56% greater likelihood that at least one other individual adopted the new technology in the treatment villages. The interpretive lens of my model suggests that locally selected nodes are more likely to be central to the profitability belief network, and theoretically optimal nodes are central to the production knowledge network. If this is true, results suggest that a policy that decreases the costs of acquiring production knowledge (theoretically optimal injection) is more effective at diffusing the technology than the benchmark, which might have changed profitability beliefs with less of an effect on learning costs.

Similarly, BenYishay and Mobarak [2014] find that a single lead farmer (LF) and groups of peer farmers (PF) differ regarding how well they diffuse technologies across social networks. PFs outperform LFs when they are incentivised to experiment and communicate the benefits of a new technology with others, and LFs outperform PFs when the converse is true. If LFs' observable actions lead their WT to change their beliefs, this would be true. However, the decrease in communication costs among PFs in the incentive treatment suggests that the more effective social learning channel in this context is one in which production knowledge is communicated with peers. Neither study, however, analyses whether any disadoption of the new technology occurred. It is possible that network-targeted farmers who disadopt create path dependencies toward equilibrium, in which a suboptimal number of households adopts the new technology.

2.7 Conclusion

I demonstrate that farmers engage in sophisticated social learning prior to deciding whether to adopt a new crop. Due to an in-sample census of network data links, the study rigorously tests eight model implications, finding consistent support for a new social learning model. Farmers are learning about two distinct objects of knowledge prior to adopting pineapple—expected profitability and production knowledge tied to a production process. Farmers update profitability beliefs by reacting to the observable adoption and disadoption decisions of WTs, but are more likely to learn production knowledge from their closest friends, STs, in their network regarding particularities of production. A different mechanism is at play regarding family members; the potential of risk-sharing confounds learning effects one might expect to observe in the data, and empirical evidence is more consistent with a resource-pooling hypothesis than a learning hypothesis among direct family members.

This paper is first in much literature on social learning and technology adoption in developing countries to analyse what farmers learn from disadopting peers. It challenges the literature to clarify thinking on the specific objects of learning that might influence an adoption decision, and the particular orientation one has in this respect leads to different policy directives. Network-based targeting policies, for example, might benefit from carefully thinking about the type of learning being propagated along social networks. Does network-based targeting do more to influence profitability beliefs or learning costs? How else might policymakers use social networks to decrease learning costs, with or without changing profitability beliefs? Incentivizing communication, as in Berg et al. [forthcoming] and BenYishay and

Mobarak [2014], might allow farmers to exchange more nuanced information with WT than is allowed by observing each others' farming practices alone. Similarly, Vasilaky [2013] studies a context in which female cotton farmers were paired with mentors, thereby increasing their ST networks.

Conceived more broadly, learning effort suggests alternative approaches that ease access to production knowledge. For example, [Duflo et al., 2015] facilitate farmer experimentation by introducing measurement devices for fertiliser application. However, can farmers be induced to aggregate data across heterogeneous plots through farmer clubs, thereby increasing the precision of their input estimates through social networks, especially when they can match network soil characteristics with their own? When production variables are not salient to farmers, as in Hanna et al. [2014], can decentralised in-service training spaces highlight previously ignored features of production processes with the assistance of an extension worker, as in Kondylis et al. [2017]?

Griliches [1957] found that diffusion is slower in regions in which profitability is lower. Similarly, Munshi [2004] argues that learning is less likely when growing conditions are heterogeneous across farmers, making it difficult to infer private returns to new technologies from the experiences of peers.[59] My model suggests an additional interpretation. When true profitability is low and returns are heterogeneous, there are likely to be higher rates of disadoption in addition to higher costs of learning [Munshi, 2004]. When disadoption is observed easily, farmers might feel less inclined to pay attention to a new technology. Griliches [1957] links the technology adoption problem with the technology innovation problem. Innovations require experimentation, and diffusion of experimentation practices are likely to correlate negatively with learning costs. Research should ask whether locally appropriate

[59]The crop system in Munshi [2004] that exhibited greater heterogeneity in production environments, rice cultivation, was also less profitable than wheat cultivation was, tied to the technology farmers learned about during analysis.

agricultural innovation, through creation of local experimentation and research networks, decreases learning costs sufficiently to encourage more farmers to acquire production knowledge.

Pineapple/Tables and Figures

Table 2.1: Network Link Distributions by Village (% by column)

Village	1	2	3	4	All
Relationship Type					
Direct Family	1.8	1.6	2.1	3.2	2.2
Extended Family	15.7	9.0	11.5	28.0	16.3
Friends in Village	82.5	89.5	86.5	68.8	81.6
Total	100.0	100.0	100.0	100.0	100.0
How long have you known this person?					
< 1 year	1.0	0.9	0.4	2.2	1.2
1-5 years	9.8	9.5	15.5	10.4	11.2
5-10 years	17.6	34.0	35.4	13.5	24.6
10+ years	71.6	55.5	48.7	73.9	63.0
Total	100.0	100.0	100.0	100.0	100.0
Frequency of Conversation					
Daily	47.7	62.8	61.5	44.4	53.7
Weekly	17.9	21.5	19.9	21.9	20.3
1-2 Times per Month	16.1	6.8	10.1	10.3	11.0
Rarely	18.2	8.9	8.4	23.1	14.9
Never	0.0	0.1	0.1	0.4	0.1
Total	100.0	100.0	100.0	100.0	100.0
Gift-giving Relationships					
Mutual gift-giving	31.7	23.5	24.2	42.7	30.8
Receive gift from	1.2	2.3	1.5	2.1	1.8
Offer gift to	3.7	2.0	1.9	4.8	3.1
No gift relation	63.4	72.2	72.4	50.4	64.3
Total	100.0	100.0	100.0	100.0	100.0
N	14,515	13,330	12,309	13,892	54,046

*Note: The number of links only includes individuals who were reported to be known personally.

Table 2.2: Relationship Strength By Village (% by column)

Relationship Strength		Village Number 1	2	3	4	All
	Not Friend	44.2	47.4	48.4	42.7	45.7
Weak Ties	Distant Friend	34.8	27.3	27.1	27.3	29.2
	Acquaintance	7.4	10.2	8.1	13.6	9.8
Strong Ties	Good Friend	11.8	12.9	13.4	12.5	12.6
	Close Friend	1.8	2.2	2.9	3.8	2.6
Total		100.0	100.0	100.0	100.0	100.0
Number of Links		21,554	22,369	17,786	19,672	81,381

Table 2.3: Relationship Type by Strength (% by column)

		Relationship Type			
Relationship Strength		Direct Family (%)	Extended Family (%)	Others in Village (%)	Total (%)
	Not Friend	1.1	3.7	21.5	18.2
Weak Ties	Distant Friend	6.4	27.2	48.3	44.0
	Acquaintance	6.3	18.9	14.2	14.8
Strong Ties	Good Friend	21.0	41.7	14.5	19.0
	Close Friend	65.2	8.4	1.5	4.0
Total		100.0	100.0	100.0	100.0
Number of Links*		1,167	8,784	44,094	54,045

*Note: The number of links only includes individuals who were reported to be known personally.

TABLE 2.4: Time-Constant Control Variables

	Village 1			Village 2			Village 3			Village 4			All Villages		
	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd
Female	124	0.45	0.50	130	0.48	0.50	142	0.54	0.50	107	0.46	0.50	503	0.48	0.50
Years of Education	124	3.35	2.17	130	3.59	3.21	141	3.06	3.23	106	3.60	2.41	501	3.39	2.83
Score of 0-8 in Literacy Test	122	5.41	3.00	126	5.29	3.31	134	4.13	3.56	106	3.75	3.38	488	4.67	3.39
Score of 0-8 in Math Test	122	5.61	2.59	126	5.83	2.60	134	5.04	2.81	106	4.64	3.09	488	5.30	2.80
Received pineapple training from extension	124	0.09	0.29	131	0.07	0.25	137	0.09	0.28	108	0.04	0.19	500	0.07	0.26
Received pineapple training from business relation	124	0	0.00	131	0.18	0.39	137	0.08	0.27	108	0	0.00	500	0.07	0.26
Received pineapple training from NGO	124	0.01	0.09	131	0.06	0.24	137	0.04	0.19	108	0	0.00	500	0.03	0.17
Risk Aversion (1-11, 11 - most risk averse)	119	7.65	1.68	124	8.73	1.95	111	8.52	2.03	105	7.99	1.90	459	8.23	1.93
Never Owned Land (to Date)	163	0.43	0.50	155	0.41	0.49	151	0.33	0.47	166	0.55	0.50	636	0.43	0.50
Measure of Slope of Land	120	14.89	13.07	129	11.93	6.20	137	11.14	7.48	101	14.73	9.17	487	13.02	9.36

Variables such as amount of schooling are not technically time-constant. However, since each individual enters the analysis in the model after turning 18 (as described in section 2.4), I can plausibly assume that such a measure is constant over the duration of the analysis.

Table 2.5: Time-Varying Control Variables

	Village 1			Village 2			Village 3			Village 4			All Villages		
	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd
1970															
Age	19	23.68	5.00	23	26.13	6.38	25	26.12	7.21	19	27.32	8.76	86	25.85	6.95
Area of Land Owned (Acres)	19	0.40	1.50	21	0.00	0.00	20	0.00	0.00	11	0.00	0.00	71	0.11	0.78
1980															
Age	57	26.11	6.58	47	29.62	8.03	45	29.40	9.41	44	28.95	9.56	193	28.38	8.43
Area of Land Owned (Acres)	49	0.40	1.33	40	0.13	0.75	38	0.06	0.36	32	0.16	0.55	159	0.20	0.88
1990															
Age	87	31.46	8.46	84	31.83	10.78	87	31.17	11.10	74	32.22	11.18	332	31.65	10.37
Area of Land Owned (Acres)	71	0.40	1.18	63	0.26	0.86	68	0.25	0.80	52	0.17	0.49	254	0.28	0.89
2000															
Age	113	37.09	11.02	119	36.34	12.54	129	34.92	12.93	101	36.90	13.09	462	36.25	12.41
Area of Land Owned (Acres)	89	0.59	1.60	87	0.64	1.40	96	0.23	0.72	73	0.25	0.80	345	0.43	1.21
2009															
Age	124	44.10	12.32	130	43.37	13.66	142	42.06	13.67	107	44.73	13.60	503	43.47	13.33
Area of Land Owned (Acres)	93	0.66	1.59	92	0.85	1.61	101	0.44	1.02	74	0.32	0.80	360	0.58	1.33

Only individuals older than 18 at time t are included in this table to correspond with the time-to-event analysis I employ in my estimation strategy.

Table 2.6: Proposed Tests for Model Implications

Model Implication	Equation Number (2.16)	Notes
1	$\rho_{ST} + \rho_{ST,I} = 0$ $\rho_{WT} + \rho_{WT,I} = 0$	For model implications 1 to 3 I indicates all years after 2004.
2	$\rho_{ST} > 0$, $\rho_{WT} > 0$	
3	$\rho_{ST} > \rho_{WT} > 0$	
4	$\rho_{ST,I} > \rho_{ST}$ $\rho_{WT,I} > \rho_{WT}$	I indicates learning capabilities, Q_i, proxied using math scores.
5	$\gamma^a_{ST} > 0$, $\gamma^a_{WT} > 0$	
6	$\gamma^d_{ST} < 0$, $\gamma^d_{WT} < 0$	
7	$\gamma^d_{WT} < \gamma^d_{ST} < 0$ $\gamma^a_{WT} > \gamma^a_{ST} > 0$	
8	$\phi_{DF} > 0$	

Table 2.7: How do peers influence beliefs?

	Coef. (Hyp.)	No Contextual Effects			Contextual Effects		
		No I	I	Indirect	No I	I	Indirect
Belief-Updating ($\mathbf{g}'_{\mathbf{k,it}}$):							
Share ST Adopters ($\mathbf{g}'_{\mathbf{ST,it}} \cdot \mathbf{a}_{\mathbf{t-1}}$)	γ^a_{ST}, (+)	0.022	0.018	0.038	0.034	0.030	0.052*
		(0.022)	(0.022)	(0.028)	(0.023)	(0.023)	(0.028)
Share ST Disadopters ($\mathbf{g}'_{\mathbf{ST,it}} \cdot \mathbf{d}_{\mathbf{t-1}}$)	γ^d_{ST}, (-)	-0.013	-0.004	0.046	-0.013	-0.003	0.055
		(0.022)	(0.022)	(0.036)	(0.026)	(0.027)	(0.037)
Share WT Adopters ($\mathbf{g}'_{\mathbf{WT,it}} \cdot \mathbf{a}_{\mathbf{t-1}}$)	γ^a_{WT}, (+++)	0.044**	0.051**	0.057***	0.038*	0.046**	0.050**
		(0.020)	(0.021)	(0.022)	(0.021)	(0.021)	(0.023)
Share WT Disadopters ($\mathbf{g}'_{\mathbf{WT,it}} \cdot \mathbf{d}_{\mathbf{t-1}}$)	γ^d_{WT}, (- - -)	-0.100***	-0.098**	-0.086**	-0.117***	-0.115***	-0.103***
		(0.038)	(0.039)	(0.038)	(0.038)	(0.039)	(0.038)
Learning (S^k_{it})	**æ**	Yes	Yes	Yes	Yes	Yes	Yes
Family Effects	**Œ**	Yes	Yes	Yes	Yes	Yes	Yes
Indirect Effects ($(\mathbf{G}'_{\mathbf{ST,i(t-1,2)}})^{2,3} \cdot \mathbf{a}_{\mathbf{t-2,3}}$ or $\mathbf{d}_{\mathbf{t-2,3}}$)		No	No	Yes	No	No	Yes
Controls	β	Yes	Yes	Yes	Yes	Yes	Yes
Contextual Effects	**ffi**	No	No	No	Yes	Yes	Yes
Correlated Effects	α_t and ν_v	Yes	Yes	Yes	Yes	Yes	Yes
MI 7 - $H_0 : \gamma^a_{WT} \leq \gamma^a_{ST}$		0.24	0.15	0.29	0.45	0.31	0.52
MI 7 - $H_0 : \gamma^d_{WT} \geq \gamma^d_{ST}$		0.03	0.02	0.00	0.01	0.01	0.00
$H_0 : \gamma^d_{WT} \leq \gamma^a_{WT}$		0.88	0.84	0.73	0.95	0.92	0.86
R-squared		0.05	0.05	0.05	0.05	0.06	0.06
Clusters		482	482	481	482	482	481
N		9946	9946	9766	9946	9946	9766

$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. OLS estimation of equation 2.16 when data are inputed to maximize equation 2.15. Model implications 5 and 6 embedded in results associated with coefficients $\gamma^a_{k,it}$ and $\gamma^d_{k,it}$ respectively. Model implication 7 tested using one-tailed Wald test. A ten percent increase in the share of WT disadopters decrease the linear probability of adoption by one percentage point in any given year. Interaction term, I, is a variable equal to one in years greater than 2003. Indirect effects are the effects attributed to the adoption and disadoption decisions of 2nd and 3rd degree ST links in periods $t-2$ and $t-3$ respectively.

Table 2.8: Can peers' experience reduce the cost of learning effort?

		No Contextual Effects			Contextual Effects		
	Coef., (Hyp.)	No I	I	Indirect	No I	I	Indirect
Learning (S_{it}^{k}):							
Number Experienced ST (S_{it}^{ST})	ρ_{ST}, $(+{+}+)$	0.002**	0.003***	0.003***	0.002**	0.003***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number Experienced WT (S_{it}^{WT})	ρ_{WT}, $(+)$	0.001	0.001	0.001	0.001	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Number Experienced ST (S_{it}^{ST}) × Post 2004	$\rho_{ST,I}$, $(-\rho_{ST})$		-0.003**	-0.003**		-0.003**	-0.003**
			(0.001)	(0.001)		(0.001)	(0.001)
Number Experienced WT (S_{it}^{WT}) × Post 2004	$\rho_{WT,I}$, $(-\rho_{WT})$		-0.000	0.000		0.000	0.000
			(0.001)	(0.001)		(0.001)	(0.001)
Beliefs ($\mathbf{g}'_{\mathbf{k,it}} \cdot \mathbf{a_{t-1}}$ or $\mathbf{g}'_{\mathbf{k,it}} \cdot \mathbf{d_{t-1}}$)	γ	Yes	Yes	Yes	Yes	Yes	Yes
Family Effects	ϕ	Yes	Yes	Yes	Yes	Yes	Yes
Indirect Effects ($(\mathbf{G}'_{\mathbf{ST,i(t-1,2)}})^{2,3} \cdot \mathbf{a_{t-2,3}}$ or $\mathbf{d_{t-2,3}}$)		No	No	Yes	No	No	Yes
Controls	β	Yes	Yes	Yes	Yes	Yes	Yes
Contextual Effects	δ	No	No	No	Yes	Yes	Yes
Correlated Effects	α_t and ν_v	Yes	Yes	Yes	Yes	Yes	Yes
MI 1 - $H_0 : \rho_{ST} + \rho_{ST,I} = 0$			0.50	0.42		0.52	0.45
MI 1 - $H_0 : \rho_{WT} + \rho_{WT,I} = 0$			0.16	0.15		0.19	0.19
MI 3 - $H_0 : \rho_{ST} \leq \rho_{WT}$		0.05	0.01	0.01	0.05	0.01	0.00
R-squared		0.05	0.05	0.05	0.05	0.06	0.06
Clusters		482	482	481	482	482	481
N		9946	9946	9766	9946	9946	9766

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. OLS estimation of equation 2.16 when data are inputed to maximize equation 2.15. Model implication 2 embedded in results associated with coefficients ρ_{ST} and ρ_{WT}. Model implication 1 and 3 tested using one-tailed Wald tests. Ten experienced strong ties increase the probability of adoption by 3 percentage point in any given year. Interaction term, I, is a variable equal to one in years greater than 2003. Indirect effects are the effects attributed to the adoption and disadoption decisions of 2nd and 3rd degree ST links in periods $t-2$ and $t-3$ respectively.

Table 2.9: MI 4: Can learning capabilities, Q_i =math score, reduce the cost of learning effort?

	No Contextual Effects			Contextual Effects		
	$S_{it}^{k} \times I$	S_{it}^{k***}	$S_{it}^{k***} \times I$	$S_{it}^{k} \times I$	S_{it}^{k***}	$S_{it}^{k***} \times I$
Learning (S_{it}^{k}):						
S_{it}^{ST}	-0.003			-0.004**		
	(0.002)			(0.002)		
$S_{it}^{ST} \times$ Math	0.008***			0.010***		
	(0.002)			(0.002)		
S_{it}^{WT}	-0.000			-0.001		
	(0.001)			(0.001)		
$S_{it}^{WT} \times$ Math	0.002*			0.002*		
	(0.001)			(0.001)		
S_{it}^{ST***}(Math Score 7 or 8)		0.005***	-0.003		0.005***	-0.004
		(0.001)	(0.003)		(0.001)	(0.003)
S_{it}^{WT***}(Math Score 7 or 8)		0.001	-0.001		0.001	-0.001
		(0.001)	(0.001)		(0.001)	(0.001)
S_{it}^{ST***}(Math Score 7 or 8) $\times$ Math			0.011***			0.011***
			(0.003)			(0.003)
S_{it}^{WT***}(Math Score 7 or 8) $\times$ Math			0.003**			0.003**
			(0.001)			(0.001)
Beliefs ($\mathbf{g}'_{\mathbf{k,it}} \cdot \mathbf{a}_{\mathbf{t-1}}$ or $\mathbf{g}'_{\mathbf{k,it}} \cdot \mathbf{d}_{\mathbf{t-1}}$)	Yes	Yes	Yes	Yes	Yes	Yes
Family Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Contextual Effects	No	No	No	Yes	Yes	Yes
Correlated Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.05	0.05	0.05	0.06	0.05	0.05
Clusters	482	482	482	482	482	482
N	9946	9946	9946	9946	9946	9946

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. OLS estimation of equation 2.16 when data are inputed to maximize equation 2.15. Interaction term, I, equals the percent of correct answers on a math test (out of 8). Variable S_{it}^{k***} indicates the number of ST or WT who scored 7 or 8 on math test (i.e. the intelligence of the peers with pineapple experience). Contextual vars of columns 5 and 6 associated with ST or WT who scored 7 or 8 on math score. Post 2004 interactions included but not reported. Own mathscore included in controls in every regression. See figure 2.9 for graphical depiction of similar regressions.

Table 2.10: MI 8: Resource Pooling Among Family Members

	Coef.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Direct Family (S_{it}^{DF}, $\mathbf{g_{DF,it}} \cdot \mathbf{a_{t-1}}$ or $\mathbf{d_{t-1}}$):								
Share DF Adopters ($\mathbf{g'_{DF,it}} \cdot \mathbf{a_{t-1}}$)	γ_{DF}^{a}	-0.048**	-0.041*	-0.007	-0.012	-0.039	-0.035	-0.010
		(0.023)	(0.024)	(0.014)	(0.014)	(0.024)	(0.024)	(0.014)
Share DF Disadopters ($\mathbf{g'_{DF,it}} \cdot \mathbf{a_{t-1}}$)	γ_{DF}^{d}	-0.072***	-0.063**	-0.028	-0.029*	-0.058**	-0.058**	-0.031*
		(0.026)	(0.027)	(0.018)	(0.017)	(0.027)	(0.027)	(0.018)
Number Experienced DF (S_{it}^{DF})	ρ_{DF}	0.017**	0.013			0.011	0.010	
		(0.008)	(0.009)			(0.009)	(0.009)	
Number Experienced DF (S_{it}^{DF}) $\times$ Post 2004	$\rho_{DF,I}$	-0.002	-0.002			-0.001	-0.000	
		(0.009)	(0.009)			(0.009)	(0.009)	
Total DF in Village ($N_{DF,it}$)	ϕ_{DF}		0.001	0.003***	0.001	0.000	0.000	0.001
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Land Size								
Total DF Land Size (Hectares)	$\phi_{DF,L}$				0.003**	0.002*	0.003***	0.004***
					(0.001)	(0.001)	(0.001)	(0.001)
Own - Average DF Land Size (Hectares)	$\beta_{L,DF}$						0.005***	0.005***
							(0.002)	(0.002)
ST,WT,EF Beliefs ($\mathbf{g'_{k,it}} \cdot \mathbf{a_{t-1}}$ or $\mathbf{g'_{k,it}} \cdot \mathbf{d_{t-1}}$)		Yes	Yes	Yes	Yes	Yes	Yes	Yes
ST,WT,EF Learning (S_{it}^{k})		Yes	Yes	Yes	Yes	Yes	Yes	Yes
EF Total		No	Yes	Yes	Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Correlated Effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared		0.05	0.05	0.05	0.05	0.05	0.05	0.05
Clusters		482	482	482	482	482	482	482
N		9946	9946	9946	9946	9946	9946	9946

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. OLS estimation of equation 2.16 when data are inputed to maximize equation 2.15. Model 1 replicates ST, WT, analysis using direct family tie (DF) networks. Model 2 includes total family numbers in village. Model 3 omits S_{it}^{DF} from analysis. Model 4 includes family land size in village. Model 5 conducts a regression among aforementioned variables. Model 6 introduces individual land size relative to the average land size of the DF network. Now, total family wealth is strongest predictor of adoption, family member disadoption strongly discourages adoption among others, and the most likely adopter *within* the family is the individual with the most amount of land.

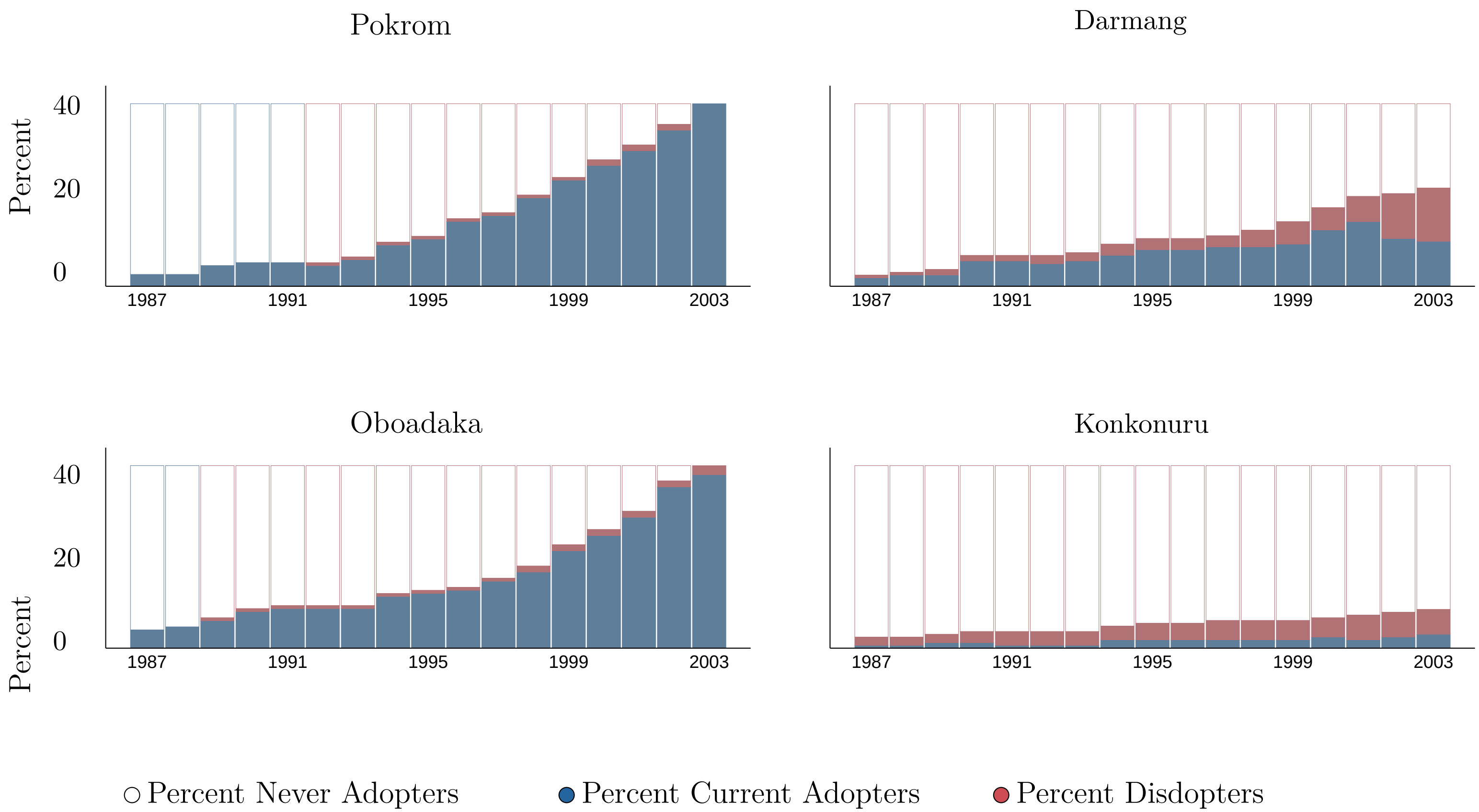
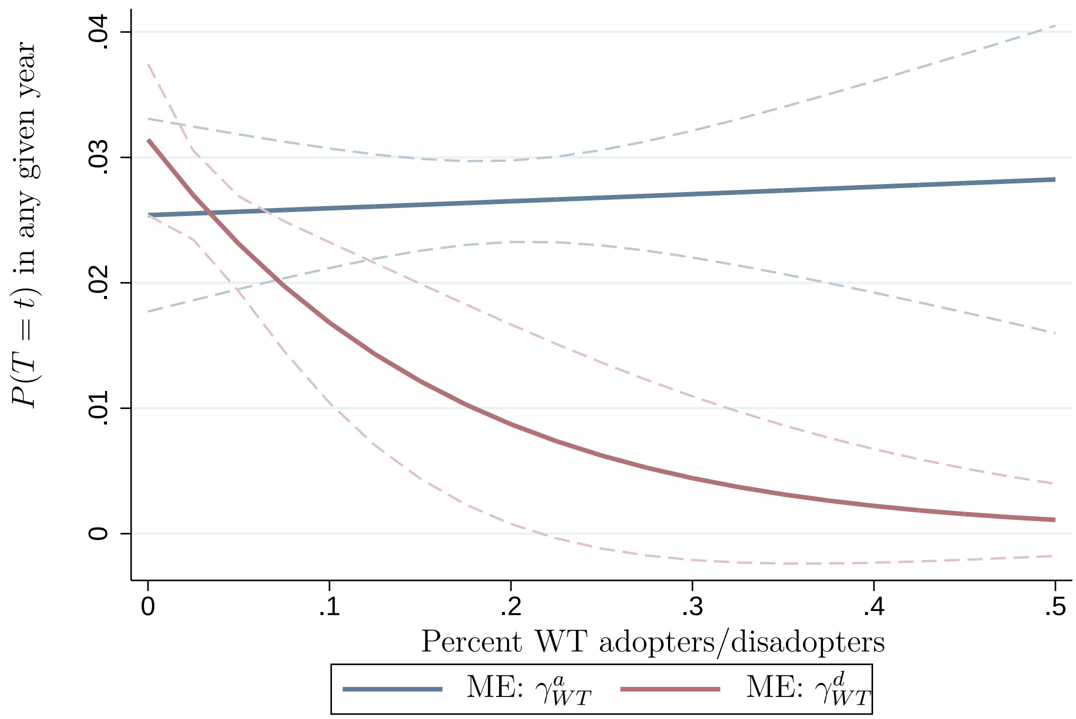
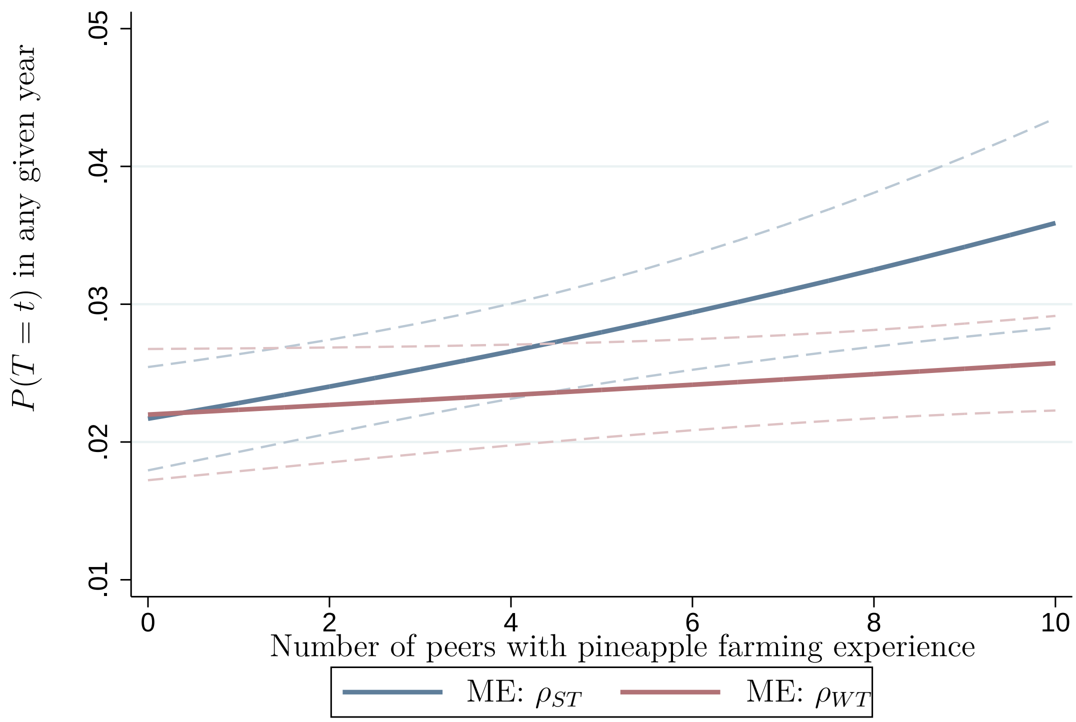


FIGURE 2.1: Share of Pineapple Adopters and Disadopters by Village



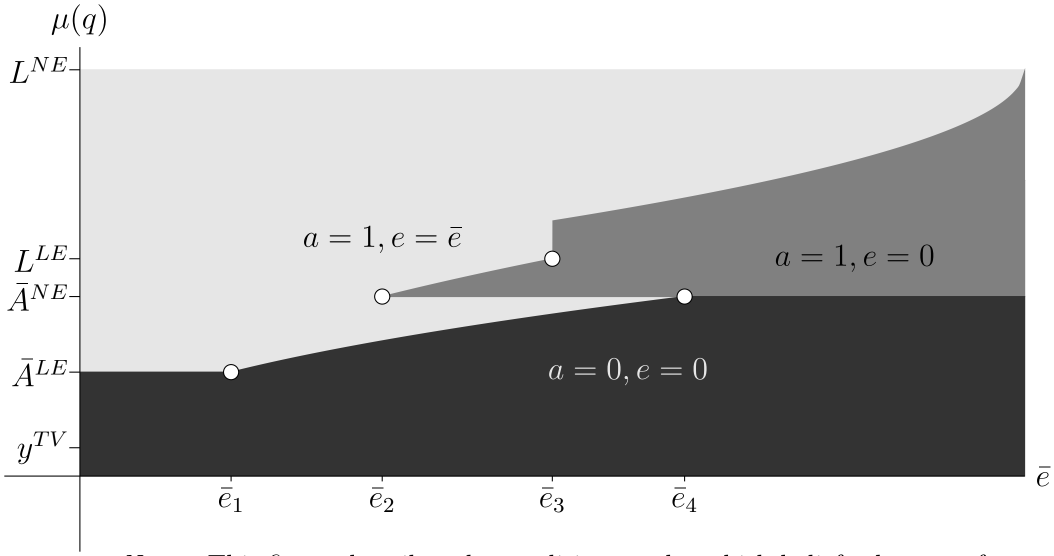
Notes: Marginal effects from logit estimation of the fully specified model (i.e., last column in tables 2.7 or 2.8). Starting from a baseline per-year adoption probability of 3%, the probability of adoption decreases by roughly 60% to 1% when 20% of weak ties have disadopted the new crop. No significant change in logit estimation of WT adopter effect.

Figure 2.2: Belief Updating from WT Decisions: Marginal Effects of Logit Estimation



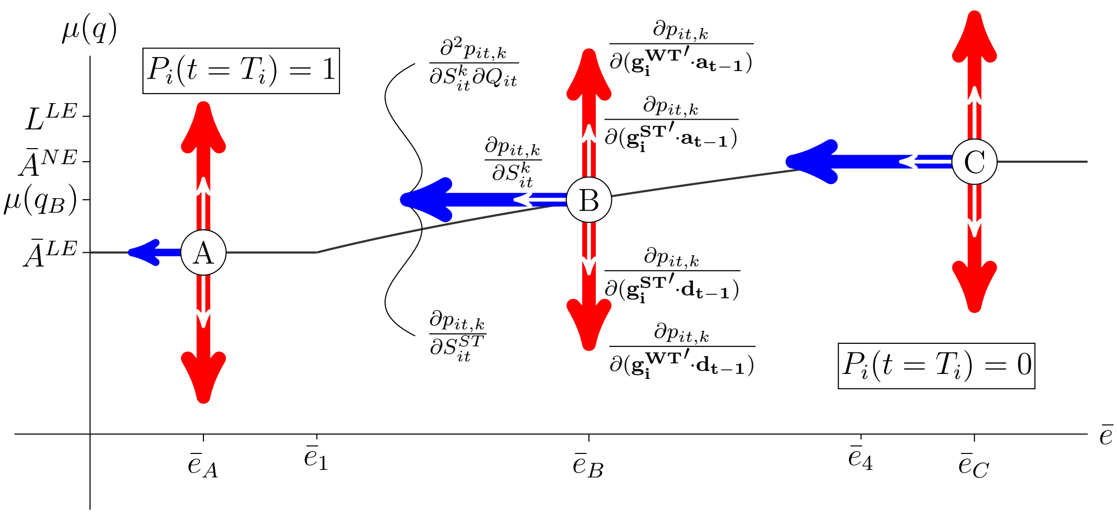
Notes: Marginal effects from logit estimation of the fully specified model (i.e., last column in tables 2.7 or 2.8). Starting from a baseline per-year-adoption probability of 2.2%, the probability of adoption increases by roughly 60% to 3.5% when an additional 10 strong ties gain experience farming pineapple (6% increase per strong tie). No significant change in logit estimation of WT adopter effect.

FIGURE 2.3: Learning Production Knowledge from Peers' Experience: Marginal Effects of Logit Estimation



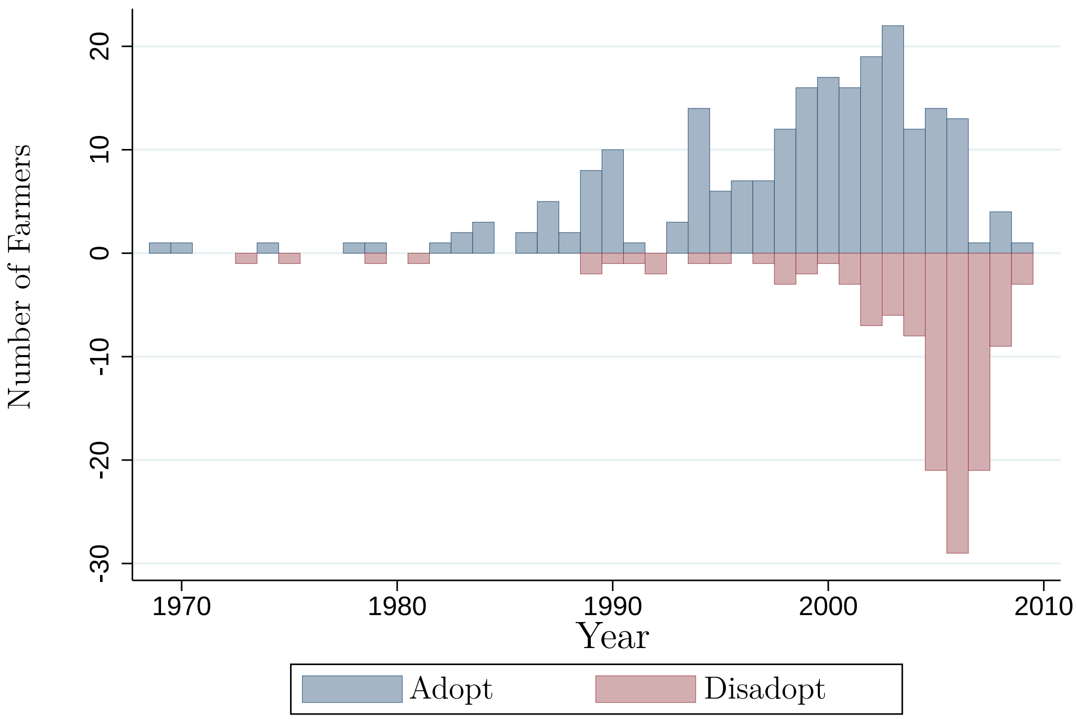
Notes: This figure describes the conditions under which beliefs about profitability ($\mu(q)$) and learning cost ($\bar{e}$) lead to adoption of the new technology. The light gray area labeled $a = 1, e = \bar{e}$ represents the parameter combinations that lead to adoption of a new technology **with** learning effort. The dark gray area labeled $a = 1, e = 0$ represents the parameter space that leads to adoption of a new technology **without** learning effort. The black area labeled $a = 0, e = 0$ represents the parameter space that does not lead to adoption. $\bar{A}^{LE}$ is the belief value at which adoption with learning effort becomes feasible; $\bar{A}^{N}E$ is the belief value at which adoption without learning effort becomes feasible. L^{LE} (L^{NE}) is the belief at which $A = L$ with (without) learning effort. I choose the following values for model parameters in constructing this graph: $L = 10$, $\bar{A} = 4$, $\gamma(0) = .2$, $\gamma(\bar{e}) = .1$, and $y^{TV} = .3$.

Figure 2.4: Graphical Depiction of Proposition 1



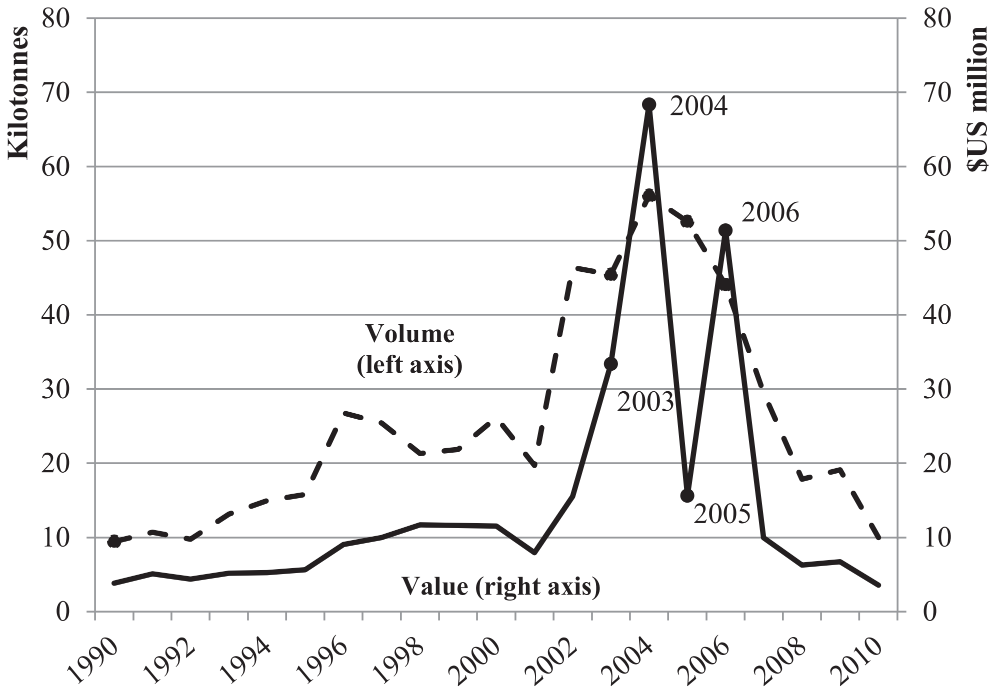
Notes: This figure describes each of the model implications discussed in section 2.2.4. The black line separates the parameter space into two mutually exclusive sets: the set of parameter combinations that lead to adoption ($P_i(t = T_i) = 1$) and the set of parameter combinations that lead to now action ($P_i(t = T_i) = 0$) for a farmer who has yet to adopt the new crop. Vertical red (white) arrows describe the effect of WT (ST) adoption ($\mathbf{a_{t-1}}$) or disadoption ($\mathbf{d_{t-1}}$) on own profitability beliefs ($\mu(q)$) through the DeGroot learning mechanism. These effects can induce (arrows pointing up) or delay adoption (arrows pointing down) for farmer i. Horizontal lines show the effect of peer adoption on decreasing the learning cost. Experienced STs can decrease learning costs to a greater extent than experienced WT. Intelligent (high Q_i) farmers are better at acquiring production knowledge from peer experiences (blue arrows).

FIGURE 2.5: Comparative Statics of Corollary 1



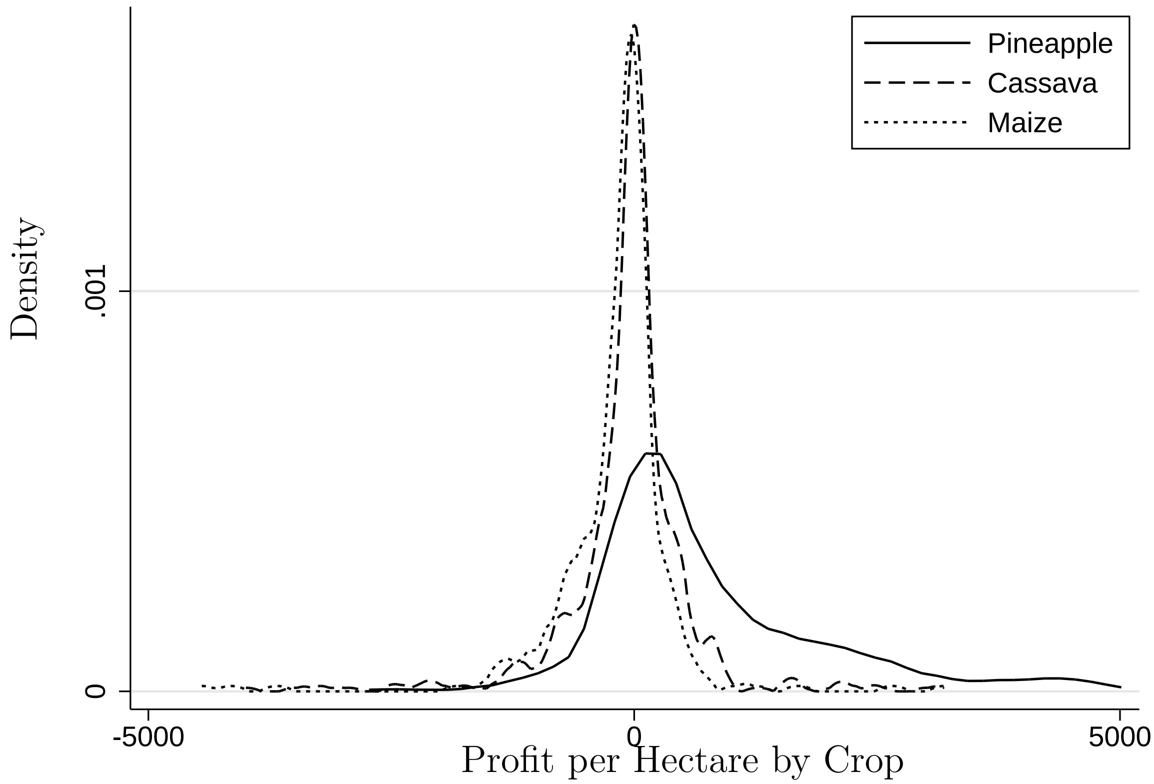
Notes: Number of additional pineapple farmers in any given year. Negative numbers (graphed using red bars) indicate the number of pineapple disadopters. The year 2004 coincided with a market crash in sweet cayenne pineapple prices, the dominant variety farmed in Ghana. See figure 2.7 for more details.

FIGURE 2.6: Year of Pineapple Adoption and Disadoption



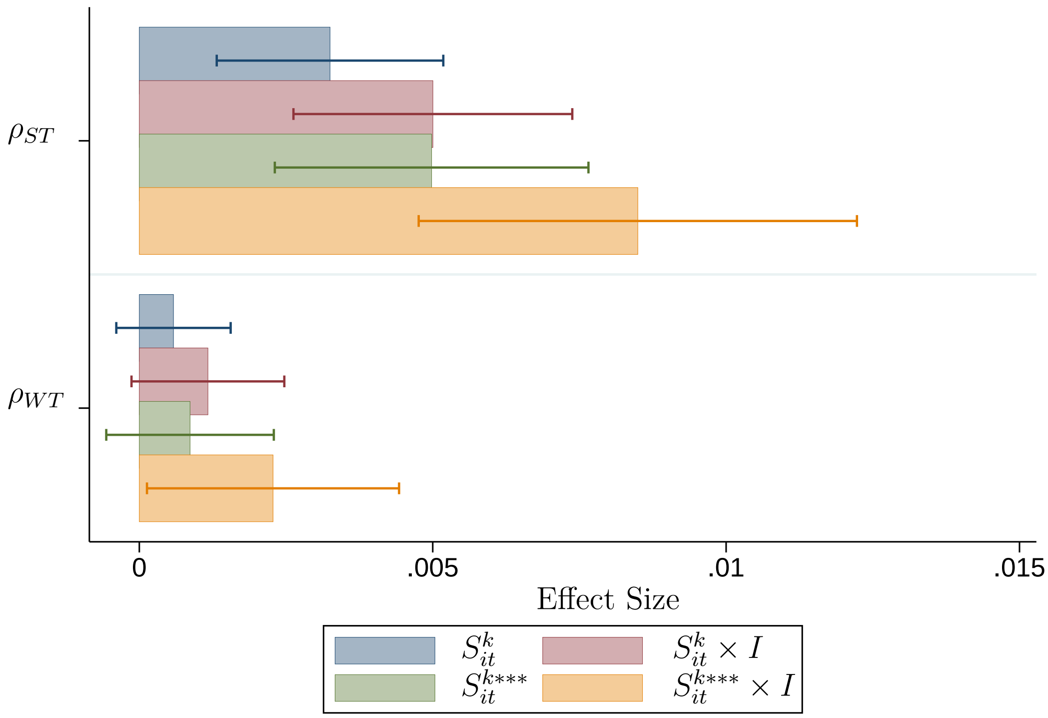
Notes: Figure sourced from Harou et al. [2017], who retrieved data from FAOSTAT in 2013. When last checked in September 2017, the same data on the FAOSTAT website used to generate this figure have been replaced with either price and quantity projections or unofficial figures in years ranging from 2004 to 2010; these data do do not accurately portray the extent of the price shock, thus I have copied figure 1 used in Harou et al. [2017] with the authors' permission.

FIGURE 2.7: Volume and Value of Pineapple Exports from Ghana



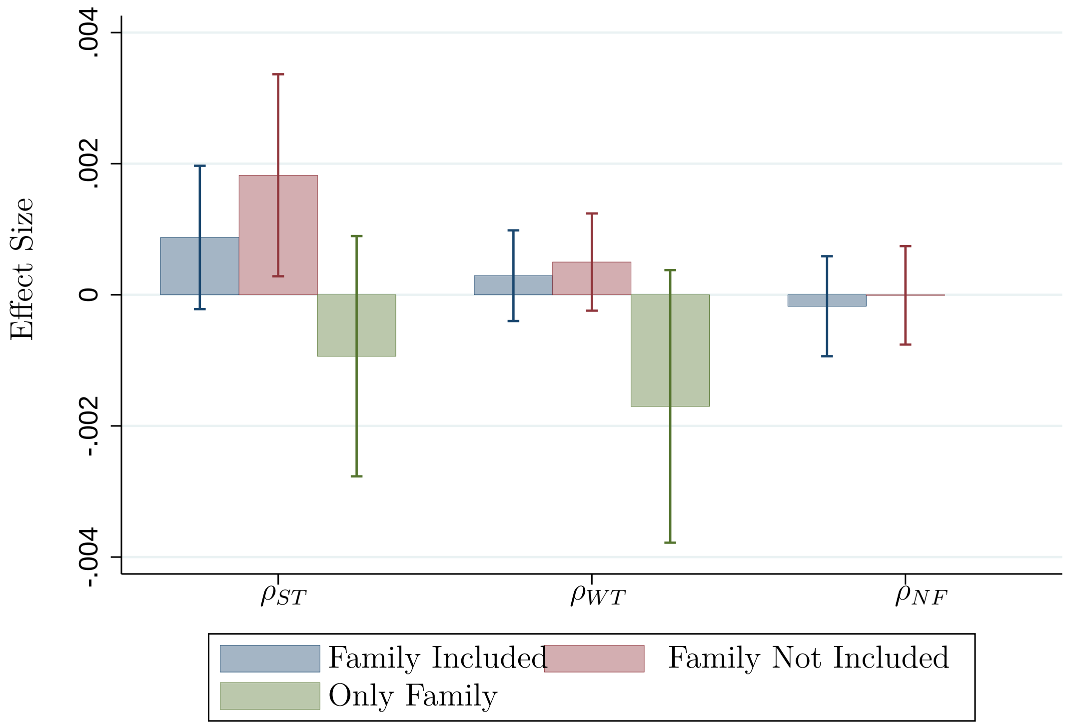
Notes: Data is sourced from Conley and Udry [2010a]. Extreme values (above 5,000 and below -5,000 GH¢) are suppressed. Kernel density estimated using Epanechnikov kernel with bandwidth = 252.7. The average (median) per hectare profit for pineapple at 745.3 (368.6) GH¢; average (median) for maize is -175.1 (-76.1) GH¢; average (median) for cassava is -56.1 (-0.9) GH¢. Profits are net of all costs, inclusive of labor costs, per acre.

Figure 2.8: Per Hectare Profit Densities



Notes: Comparison of effect size with and without math score interactions. I equals the percent of correct answers scored on a math test (out of 8 questions). S_{it}^{k***} signifies summation of pineapple adopters whose math scores equal 7 or 8 (i.e., intelligent peers who adopt pineapple). Learning more pronounced if own math score is high, but especially if together with high peer math score.

FIGURE 2.9: Testing MI 4: Higher Math Scores = Less Costly Learning?



Notes: Comparison of effect size when friendship network, $\mathbf{G_t^k}$, includes family ties ("Family Included") vs. when family ties are not included ("Family Not Included"). "NF" indicates individuals in friendship network who are reported not to be friends (corresponding variable S_{it}^{NF}). Also included is a network consisting of family ties only, separated by whether they are reported to be ST, WT, or NF. Throughout the analysis, the primary friendship network does not include family ties (family ties are treated separately). Reporting of "Only Family" category in which family members are listed as being NF is suppressed due to excessively large confidence intervals. Learning cost decreases as friendship tie increases in social proximity, though is confounded by the inclusion of family relations.

FIGURE 2.10: Learning Effect, ρ_k When Including/Excluding Family Ties

CHAPTER 3

ALTRUISM AND INSURANCE IN COSTLY SOLIDARITY NETWORKS

3.1 Introduction

Social solidarity networks have long been understood to play a central role in village economies. There can be both altruistic and self-interested drivers behind such networks' functioning (Ligon and Schechter [2012]). Although the possibility of altruism has been accommodated in some work within that literature (notably Foster and Rosenzweig [2001]), at least since Popkin [1979] and Posner (1980), the dominant framework for social scientists' understanding of transfers within social networks has rested on self-interested dynamic behavior, commonly framed as self-enforcing informal insurance contracts [Fafchamps, 1992, Coate and Ravallion, 1993, Townsend, 1994]. In this tradition, larger networks expand one's social insurance pool, thereby stabilizing consumption, provided that income realizations are publicly observable so as to ensure enforceability of the informal insurance contract [Ambrus et al., 2014]. A nice implication of this framework for public policy is that social networks should (at least partially) correct targeting errors in publicly observable transfer programs, as non-recipients who have suffered adverse shocks will approach recipients within their network to share their windfall gains [Angelucci and De Giorgi, 2009].

A related but distinct literature emphasizes the dark side of sharing within social networks, as social pressures can place significant demands on those who enjoy income growth, discouraging investment and potentially even trapping households in poverty [Platteau, 2000, Sen and Hoff, 2006, Jakiela and Ozier, 2016, Squires, 2017]. This contrary perspective raises important questions about prospective limits to the value of extensive social networks and of full transparency of individual outcomes.

In this paper we integrate these two streams of thought on the roles social solidarity networks play in village economies. We follow Foster and Rosenzweig [2001] in modeling limited commitment risk pooling allowing for altruistic preferences. Our model includes two key refinements, however, reflecting how our research subjects in rural Ghana describe to us the operation of sharing arrangements within their social networks. First, we model an impure, 'warm glow' component to altruistic preferences (following Andreoni [1990]) that diminishes with the more gifts one gives within one's network. While individuals might vary in the extent of their altruism, everyone faces some limit to the pleasure they derive from beneficence. If giving is costly and the returns to giving diminish, there then emerges some point at which even altruistic individuals cease giving because of the social taxation pressures they face. We term this the 'shutdown hypothesis'. Second, altruistic individuals would like to target their giving toward the neediest members of their social network. But when stochastic income realizations are publicly observable, the demands of less needy members of the solidarity network to share in a windfall can crowd out giving to those with greater need. These two key refinements thereby overturn two key implications of the canonical model of informal insurance - that a larger network and observable income are better - and reflect findings from the literature on social taxation. Nonetheless, within the links that endogenously remain, full risk pooling should obtain, so the social solidarity network retains its key function in distributing stochastic income realization across a network, thereby smoothing consumption.

We take these findings to unique data from southern Ghana, where over the course of a year we randomized private and public bimonthly cash payments to subjects whose gift networks we had previously mapped. These exogenous income shocks enable us to test the predictions of our analytical model. We rely primarily on regressions of giving within subjects' social networks as function of exogenous (randomized) private and public winnings.

We corroborate those findings with regressions of how subjects' consumption varies with winnings within one's network and with dyadic regressions reflecting the flows between any two subjects.

Several striking empirical findings emerge, each consistent with the predictions of the analytical model but not with the canonical model of informal insurance. First, the average size of gifts one gives within one's network are larger for private than for public windfall gains. This indicates more targeted giving when altruistic behavior dominates because the unobservability of one's winnings attenuates network demand to honor the informal insurance contract. Furthermore, this confirms the existence of altruistic motives in social solidarity networks. In the absence of altruistic preferences and observability of the income shock, one would never share private winnings. Second, and relatedly, those with unobservable income gains target their giving to the neediest households within their networks. Private, altruistic giving is more sensitive to correcting maldistribution than is public sharing. Third, the number of gifts given is larger for public than for private winnings, consistent with greater network demand for transfers. Fourth, the shutdown hypothesis appears to hold. Winners of publicly revealed cash prizes cease making transfers at all when they have too large a network. Finally, among those who maintain active gift giving, we cannot reject the null hypothesis of full risk pooling. Like prior studies that similarly find evidence supporting efficient risk sharing within limited networks (e.g.,Vanderpuye-Orgle and Barrett [2009], Mazzocco and Saini [2012], Ambrus et al. [2017]), these findings underscore that insurance motives parallel altruism within social solidarity networks.

Consistent with the literature on social taxation [Platteau, 2000, Sen and Hoff, 2006, Jakiela and Ozier, 2016], these results highlight the limits to social networks as channels for managing income shocks as well as the trade-offs inherent to transparency in transfer programs. Although observability of income is essential in informal insurance arrangements among purely self-interested agents, observability may impede altruistic agents' ability to focus their giving on the most needy as they are compelled to respond to demands for assistance from the less needy within their network. Meanwhile, we also confirm that within the social networks that agents voluntarily maintain, consumption is indeed stabilized through near-complete risk pooling that is statistically

Our findings have practical policy implications, especially for cash transfer programs which have, over the past decade or two, become the foundation for social protection programs throughout the developing world. For example, if networks are sufficiently well-connected and populations are motivated by the well-being of others in the network, then transparency may limit the efficiency of redistributive behaviors within networks. Angelucci et al. show that Progresa transfers are pooled by family networks to finance consumption and investment and Advani [2017] shows using experimental data from Pakistan that poverty traps can exist at the network level. Simons [2016] shows that community targeting of a social safety net program is pro-poor relative to centralized targeting. These results suggest that communities in many parts of the world have intimate knowledge of their members' needs and can potentially allocate resources more efficiently than state institutions [Alderman, 2002, Bowles and Gintis, 2002]. However, Vanderpuye-Orgle and Barrett [2009] warn that within-community transfers may not benefit "socially invisible" community members — this evidence may, however, be taken with the caveat that exclusion from risk-sharing social networks may also be driven by reputation or punishment for past infringements within the community.

Combined with the above studies, our evidence suggests that governments should tread a careful path when considering the transparency of social safety net transfers. Transparent cash transfers can decrease the opportunity cost of default from potentially efficient risk-sharing networks while also providing a means of triggering social taxation that may deter investment. At the very least, governments should not treat communities as a "black box" and should make efforts to understand and measure the quality of social connections and degree of participation in social networks.

This paper proceeds by first discussing the risk-sharing model that generates the predictions we test in the data in section 3.2. Then, we discuss the data in section 3.3. In section 3.4 we present results from our preferred specification and conduct analysis of dyadic data in section 3.5. Section 3.6 concludes by summarizing our findings and providing pathways for future research.

3.2 The Model

Environment. We introduce 2 agents, $i = \{1, 2\}$ receiving stochastic incomes, $y_i(s_t) \geq 0$ that depend on the state, s_t, realized in period t — a sequence of the state history is characterized by $h_t = \{s_1, s_2, ..., s_t\}$.[1] We model history-dependent transfers from household 1 to household 2, $\tau(h_t)$, when both households have gift-networks with $g_1 = g_2 \geq 1$ other households. Depending on the realization of a particular state, households will receive $g_i p_i(s_t)$ different gift-requests from their network, where $0 \leq p_i(s_t) \leq 1$ reflects the unconditional probability that a given household in one's network will request a transfer in period t. To focus attention on transfers between households 1 and 2, we assume that net transfers with all other households in one's network equals zero for now. Thus, net income for household 1 is $y_1(s_t) - \tau(h_t)$ and net income for household 2 is $y_2(s_t) + \tau(h_t)$. If $\tau(h_t) > 0$, then household 1 (2) is a net sender (receiver) of transfers. Otherwise, if $\tau(h_t) < 0$ household 1 (2) is a net receiver (sender) of transfers.

[1] The assumption of stochastic exogenous income is reasonable in our empirical context since we distribute cash prizes randomly across the sample.

Preferences. Following Foster and Rosenzweig [2001], we assume households hold altruistic preferences towards each others' single-period utilities. We introduce individual i's altruistic preferences by assuming that household single-period utility is separable in own and other household consumption. Single-period utility for household 1 is reflected in the following equation:

$$\begin{gathered} u_1(c^1) + \gamma_1(g_1, s_t)u_2(c^2) \\ \text{such that } 0 \leq \gamma_1(g_1, s_t) \leq 0.5 \end{gathered} \tag{3.1}$$

and single-period utility for household 2 can be written in symmetric fashion. $u_1()$ and $u_2()$ are increasing and concave $\gamma_1(g_1, s_t)$ represents the altruism weight household 1 holds towards 2.

We diverge from others in that we characterize altruistic preferences as a function of a household's "altruism stock" and their transfer-network size. The altruism weight diminishes as a household's period-specific gift-requests increase, which in turn rely on a household's gift-giving network size, g_i, and the probability that it will be requested to provide transfers to other households, reflected in $p_i(s_t)$. Specifically, altruism weights consist of a fixed, or "pure," component, $\bar{\gamma}_1^F \geq 0$, and a warm-glow [Andreoni, 1990], or "impure," component $\bar{\gamma}_1^W \geq 0$. Again for household 1, we represent these components of altruism in the following manner:

$$\gamma_1(g_1, s_t) = \min\{\bar{\gamma}_1^F + \frac{\bar{\gamma}_1^W}{g_1 \cdot p_1(s_t)} \mathbb{1}(\tau(h_t) \neq 0), \overline{\gamma}_1\} \tag{3.2}$$

where $\mathbb{1}(\cdot)$ is an indicator function equal to one when there is a transfer between households 1 and 2, and $\overline{\gamma}_1$ places an upper bound on household 1's altruism weight towards household 2 so that altruism does not rise to arbitrarily large levels when $p_1(s_t)$ is small.

Explicitly stated we assume here that the amount of warm-glow altruism household 1 holds towards household 2 is a decreasing function of the total number of household 1's period t gift-obligations, $g_1 \cdot p_1(s_t)$. This reflects the idea that warm-glow is diminishing in the number of discrete transfers each household participates in — intuitively, the novelty of warm-glow wears off as transfers become more common-place. Without loss of generality, we will set $\bar{\gamma}_1^F = 0$ and focus our analysis around warm-glow altruism — thus, when we speak of altruism moving forward, we are no longer referring to "pure" altruism. Intuitively, and taken together, each household is altruistic towards others but is not unlimitedly so. Households can vary in the "stock" of altruism (or altruistic capital as in Ashraf and Bandiera [2017]) they possess, but will be limited in the degree of altruism they exercise towards other households.

Dynamic Payoffs and Transfer Choices. At period t, households seek to maximize their expected lifetime utility, which requires agreeing upon a history-contingent transfer contract that is preferable to zero transfers across all states. Thus, we assume that households compare payoffs from the dynamic contract to payoffs from a no-transfer rule.[2] To set up the household's problem, we define $U_1(h_t)$ as 1's expected discounted utility gain from the risk-sharing contract with 2 relative to a no-transfer rule after history h_t:

$$\begin{aligned} U_1(h_t) = \quad & u_1(y_1(s_t) - \tau(h_t)) - u_1(y_1(s_t)) \\ & + \gamma_1(g_1, s_t) u_2(y_2(s_t) + \tau(h_t)) - \gamma_1(g_1, s_t) u_2(y_2(s_t)) \\ & + \mathbb{E} \sum_{k=t+1}^{\infty} \delta^{k-t} \left\{ \begin{array}{l} u_1(y_1(s_k) - \tau(h_k)) - u_1(y_1(s_k)) \\ +\gamma_1(g_1, h_t) u_2(y_2(s_k) - \tau(h_k)) - \gamma_1(g_1, h_t) u_2(y_2(s_k)) \end{array} \right\} \\ & - \alpha_1(g_1) \end{aligned} \tag{3.3}$$

where δ represents the dynamic discounting factor. $\alpha_1(g_1)$ represents a second way in which our model diverges from others' — it is the incremental cost to household 1 of maintaining

[2] Households in Foster and Rosenzweig [2001] revert to a sequence of history-dependent Nash equilibria (SHDNE) in which transfers are maintained even when a household defaults from the contract. Such an environment is not crucial for the type of analysis we conduct in our study. Nevertheless, appendix section B.1 shows how one can adapt our own model to reflect such SHDNE default transfers.

a gift-giving link with household 2 given network size g_1. We assume that the cost of maintaining such a link is convex in network size and can be thought of as the effort required to maintain a social bond and, for example, awareness of household 2's realized income. The contract is enforced if the expected discounted utility surplus is nonnegative. The contract requires an implementability constraint that states that gains from the contract be at least as high as the no-transfer rule: $U_1(h_t) \geq 0$ and $U_2(h_t) \geq 0$. Together, the economic environment, payoffs and transfer decision represent a simultaneous game in which agents seek to find a contract that can be implemented in the presence of limited commitment and no external enforcement mechanism.

Limited Commitment Contract Solution. Following Foster and Rosenzweig [2001] and Ligon et al. [2002], the solution to the utility maximization problem will be a dynamic program in which the current state is given by s out of the set of all states ($s \in \{1, 2, ..., S\}$), and targeted discounted utility gain for household 2, U_2^s, is given.[3] Choice variables in the programming problem will be consumption assignments c_1, c_2 and the continuation utilities U_1^r and U_2^r for each possible state r, resembling the next period. This enables us to write the value function for household 1 as dependent on current target utilities and collective resources: $U_2^s, \{y_1(s) + y_2(s)\}$. Formally, we write the dynamic programming problem as

$$\begin{aligned} U_1^s(U_2^s) = \quad \max_{\tau_s,(U_1^r,U_2^r)_{r=1}^S} \quad & u_1(y_1(s) - \tau_s) - u_1(y_1(s)) \\ & + \gamma_1(g_1(s))u_2(y_2(s) + \tau_s) - \gamma_1(g_1(s))u_2(y_2(s)) \\ & - \alpha_1(g_1) + \delta \sum \pi_{sr} U_1^r(U_2^r) \end{aligned} \tag{3.4}$$

[3] U_2^s is defined by equation B.2 when all subscripts with 1 are replaced with a 2 and vice versa.

subject to

$$\lambda: \quad u_2(y_2(s) + \tau_s) - u_2(y_2(s)) \tag{3.5}$$
$$+ \gamma_2(g_2(s))u_1(y_1(s) - \tau_s) - \gamma_2(g_2(s))u_1(y_1(s))$$
$$- \alpha_2(g_2) + \delta \sum_{r=1}^{S} \pi_{sr} U_2^r \geq U_2^s$$

$$\delta\pi_{sr}\mu_r: \quad U_1^r(U_2^r) \geq \underline{U}_1^r = 0 \quad \forall r \in S \tag{3.6}$$

$$\delta\pi_r\phi_r: \quad U_2^r \geq \underline{U}_2^r = 0 \qquad \forall r \in S \tag{3.7}$$

$$\psi_1: \quad y_1(s) - \tau_s \geq 0 \tag{3.8}$$

$$\psi_2: \quad y_2(s) + \tau_s \geq 0, \tag{3.9}$$

where π_{sr} represents the probability of state r occuring. Equation 3.5 says that transfer and future utility allocations will satisfy the promise-keeping constraint. Equations 3.6 and 3.7 state that allocated utility in any state r will be at least as high as the lower bound utility household 1 and, respectively, 2 can receive via defaulting to the no-transfer arrangement. Equations 3.8 and 3.9 place non-negativity constraints on consumption allocations in period s. The actual contract can be computed recursively, starting with an initial value for U_2^s.

The concavity of the dynamic programming problem renders the first-order conditions both necessary and sufficient to obtain a solution. Thus, the evolution of the ratio of marginal utility (re-inserting t subscript), together with the envelope condition, characterizes the optimal contract:

$$\frac{u_1'(y_1(s_t) - \tau(h_t)) + \gamma_1(g_1(h_t))u_2'(y_2(s_t) + \tau(h_t))}{u_2'(y_2(s_t) + \tau(h_t)) + \gamma_2(g_2(h_t))u_1'(y_1(s_t) - \tau(h_t))} = \lambda + \frac{\psi_2 - \psi_1}{u_2'(y_2(s_t) - \tau(h_t)} \tag{3.10}$$

$$-U_1^{r\prime}(U_2^r) = \frac{\lambda + \phi_r}{1 + \mu_r}, \quad \forall r \in S \tag{3.11}$$

$$\lambda = -U_1^{s\prime}(U_2^s). \tag{3.12}$$

Taken together, these three conditions imply that a constrained-efficient contract can be characterized in terms of the evolution over time of λ, where $-\lambda$ is the slope of the Pareto frontier.[4] For each state s, there is a history independent interval $[\underline{\lambda}_s, \overline{\lambda}_s]$ that constitute the set of implementable contracts in state s. The lower bound value is the point at which household 1 is indifferent between participating in a risk-sharing contract and default — the upper bound reflects the symmetric position for household 2. The exact value of $\lambda(h_{t+1})$ is history dependent and evolves according to the value of $\lambda(h_t)$ in the following manner

$$\lambda(h_{t+1}) = \begin{cases} \underline{\lambda}_s \text{ if } \lambda(h_t) < \underline{\lambda}_s \\ \lambda(h_t) \text{ if } \underline{\lambda}_s \leq \lambda(h_t) \leq \overline{\lambda}_s \\ \overline{\lambda}_s \text{ if } \lambda(h_t) > \overline{\lambda}_s. \end{cases} \tag{3.13}$$

Given this contract structure and assumptions on utility parameters and income values, numerical solutions for all interval endpoints can be obtained by solving an $S \times 2$ dimensional non-linear system of equations.

Figure 3.1 describes the intuition behind this contract structure using a stylized example. Suppose that in an initial period, t, a state is realized in which household 1 receives

[4] For a formal proof, see Ligon et al. [2002] and Thomas and Worrall [1988]. The extension to the case with altruistic preferences is straightforward as noted by Foster and Rosenzweig [2001].

income $y_1(s_t) = 2$ and household 2 receives $y_2(s_t) = 1$.[5] If the two households follow the contract structure in equation 3.13, then each household will weigh participation in risk-sharing against the payoff received when they default from such a contract. Household 2 will only consider this contract if $\lambda(h_t)$ is greater than $\underline{\lambda}_{zv}$ — the point at which household 2 is indifferent between defaulting and participating in the risk-sharing contract (discounted utility surplus equal to zero). Household 1 will have a similar payoff structure when $\lambda(h_t) = \overline{\lambda}_{zv}$. Both households will prefer risk-sharing if they can settle on a dynamic contract between these two numbers. Suppose the realized state in period $t+1$ is zz, where $y_1(zz) = y_2(zz) = 1$. If altruistic preferences (and discount rates) are such that the contract intervals for the realized state in $t+1$ does not overlap with the state in t (left panel in figure 3.1), the surplus will be divided according to $\lambda(h_{t+1}) = \underline{\lambda}_{zz}$. If the contract intervals do overlap, then , $\lambda(h_{t+1}) = \overline{\lambda}_{zv}$. Notice that this results in a division of the surplus in which both households strictly benefit relative to default (i.e., closer to full consumption smoothing).

Income shocks. We now add more structure to the model to study the importance of the transparency of cash transfers. Let us define two types of exogenous income shocks: 1) privately revealed cash prizes (denoted by v) and 2) publicly revealed cash prizes (b). Households that do not receive cash prizes experience zero exogenous income shocks (z). Thus, there are potentially nine different states that can be realized, though we limit our analysis to states in which only up to one household receives a prize of any type: neither 1 nor 2 receive a prize (zz), 2 receives a private prize (vz), 2 receives a public prize (bz), 1 receives a private prize (zv), and 1 receives a public prize (zb).[6] Explicitly, here we are assuming that the prize-winning household receives a higher income than the non-prize winning household and the prizes are equal in value:

[5] In later simulations, this income combination will be referred to as state zv

[6] There are four additional combinations that can occur in principle: bb, vv, bv, and vb. We are primarily interested in analyzing the transfer behaviors of lottery winners to those who did not win a lottery, thus we exclude these four states from our analysis to preserve simplicity.

Assumption 9 (Prize-winners Have Higher Incomes)

$$y_1(zv) = y_1(zb) = y_2(vz) = y_2(bz) > y_1(zz) = y_1(vz) = y_1(bz) = y_2(zz) = y_2(zv) = y_2(zb)$$

Let us assume that the probability of receiving a transfer request, $p_i(s_t)$, is highest when a household wins a publicly revealed prize. In other words,

Assumption 10 (Observability of Income)

$$p_1(zb) > p_1(s') \textit{ for all } s' \neq \{zb\} \textit{ and } p_2(bz) > p_2(s'') \textit{ for all } s'' \neq \{bz\}.$$

We argue that households who receive easily observable positive income shocks are more likely to be approached by others to uphold their end of an informal gift-giving obligation. This assumption is supported by evidence in similar contexts (e.g., Jakiela and Ozier [2016] and Squires [2017]) in which participants in behavioral experiments willingly spend part of their payoff to allow winfall income gains to be hidden from their peer group. This assumption implies that the warm-glow altruism weight household 1 holds towards household 2, for example, decreases when household 1 wins a publicly revealed lottery.

3.2.1 Model Simulations

Given the complexity of the state-space, it is not possible to analytical explore solutions to this model. We are, however, fundamentally interested in how the risk-contract depends on the size of the gift giving network g_1 and the public or private nature of the prize in the realized state — thus, we explore numeric solutions using set values for model parameters while allowing network size to vary. We find that as network size increases, the marginal utility of participating in a risk-sharing contract is decreasing in network size, but is decreasing at a faster rate in the state when a household wins a public prize. This, combined with the cost of maintaining a gift-giving link will result in a gift-giving "shutdown" — beyond a certain network size threshhold, if requests for gifts are too large, then the household will not give any gifts. Additionally gift-transfers will in most cases be **larger** when a household wins a privately-revealed prize.

For the purposes of the simulation, we use log-utility for both household 1 and 2's single-period utility over consumption and use the following values for the model parameters. When a household wins a prize their income is equal to 2, e.g., $y_1(zv) = 2$, otherwise income is equal to 1, e.g., $y_1(zz) = 1$. Warm-glow altruistic capacity is set at $\overline{\gamma}_1^W = \overline{\gamma}_2^W = 2.5$ for both households. Transition probabilities are $\pi_{zz} = 0.3$, $\pi_{zv} = \pi_{zb} = \pi_{vz} = \pi_{bz} = 0.175$, which reflect that the most probable outcome is the case in which neither household wins a prize (zz) — all other states transpire with equal probability. When a household receives a publicly revealed prize, it will receive gift requests from all network members, i.e., $p_1(zb) = p_2(bz) = 1$. Otherwise, the probability that any given gift-network household requests a gift is $p_1(zz) = p_2(zz) = p_1(bz) = p_1(vz) = p_1(zv) = p_2(zb) = p_2(zv) = p_2(vz) = 0.2$. Finally, the discount rate is set to $\delta = 0.65$ for both households.

Without loss of generality, we focus our analysis on household 1's behavior. Figure 3.2 shows the evolution of the optimal (log) contract intervals as network size increases. At low network-size values, less than 4, the contract intervals overlap and are unchanging — they are unchanging because we limit warm-glow altruism towards household 2 to a maximum of 0.5. Once network size increases beyond 4, the influence of warm-glow altruism decreases in the state in which household 1 wins a publicly revealed lottery — zb. The lower- and upper-bound intervals start to increase until they no longer overlap with state zz and then with state zv. In our example, the contract intervals in state zz and zv overlap over the entire domain in figure 3.2.

Figure 3.3 shows the resulting discounted lifetime expected utility of such a contract when the initial state is either zv or bz and when household 1 extracts all the possible surplus — in other words, in the initial state, we select $\lambda(h_1) = \underline{\lambda}(s_1)$ since household 1 extracts the highest surplus when household 2's surplus is set to zero. Here, we see that discounted utility in state zb is less than discounted utility in state zv throughout the domain — this is due to the lower warm-glow altruism one experiences when encumbered with a higher number of gift-requests. Additionally, discounted utility decreases at a faster rate in the zb state until the zz and zb contract intervals cease to overlap — at this point, there is a slight jump in discounted utility in the zb state. However, after this jump, utility in the zb state continues to decrease at a faster rate. Figure 3.3 also includes a plot of the cost of maintaining one's gift-giving ties, $\alpha(g_1)$. Once discounted utility falls beneath this line, household 1 will shut down all giving to other households when state zb is realized.

3.2.2 Model Implications

These features of the model lead to our first empirical prediction:

Prediction 1 (The Shut-down Hypothesis) *Households with large gift-giving networks that experience positive publicly-revealed income shocks are more likely to "shut down," resulting in lower levels of transfers to others.*

Figure 3.4 uses gift transfers between households 1 and 2 to show the empirical implications of the shut-down hypothesis. Notice that at low values for gift-networks, household 1 transfers the same amount to household 2 regardless of being in state zv or zb. However, as the network size increases, transfer amounts start to decrease until they are equal to zero at the shutdown threshold and beyond. This relationship leads to two additional empirical implications:

Prediction 2 (Privately Revealed Prize = Higher Average Transfer Value) *The average gift value is higher in households that win privately revealed prizes than households that receive publicly revealed cash prizes.*

Prediction 3 (Publicly Revealed Prize = Higher Number of Gifts Given) *The average number of gifts given is higher in households that win publicly revealed prizes prior to passing the shutdown threshold.*

The above two predictions also imply that the total value of gifts out of households who win publicly revealed prizes are higher than the total value of gifts given from other households prior to the household reaching its shut-down threshold. This is easily shown by multiplying the average transfer value by the number of gift-obligations in period t (see appendix figure B1 for a graphical representation). The prediction can be stated as:

Prediction 4 (Prior to shut-down = Larger Volume of Transfers After Public Prize) *Prior to reaching their shut-down threshold, the volume of gifts given by households who win publicly revealed income will be larger than the volume of gifts given by households who win privately revealed income.*

So far we have discussed how the model generates predictions regarding the gift-transfer behavior of household 1. Naturally, if household 2 receives gifts from household 1, we should be able to symmetrically identify changes in household 2's consumption as a function of household 1's lottery winnings. This implies that household 2's consumption levels will be higher on average when their gift-giving network wins a cash prize. However, since transfers are predicted to be higher when the peer household wins a private lottery, it is likely that the effect will only be observed in such a state. Furthermore, since household 1's marginal utility is decreasing in household 2's consumption, we should see stronger patterns of gift-giving through the private lottery when the income gap between households 1 and 2 is large. It is straightforward to show via simulation that average transfer sizes increase as the gap between 1 and 2's per-period income increases.[7] This leads to the final prediction:

Prediction 5 (Consumption Increasing in Others' Winnings) *A household's per-capita consumption is an increasing function of its peer-network's average private lottery winnings. It may be an increasing function of its peer-network's public lottery winnings if its peers do not experience a shutdown in giving (i.e., peers have small gift-giving networks).*

3.3 Data and Descriptive Evidence

We combine a field experiment with household surveys to construct the data used in the analysis. The field experiments were conducted between March and October 2009 in conjunction with a year-long household survey in four communities in Akwapim South district of Ghana's Eastern Region. This district lies some 40 miles north of the nation's capital, Accra, but is sufficiently far away that only a handful of respondents commute to Accra for work. The sample consists of approximately 70 households from each of the four communities.[8] Individuals in the sample include the household head and his spouse.[9] There

[7] Similarly, one could add one more income-realization possibility to the state space — negative income shock — to generate relevant predictions. This would likely over-complicate the model for our purposes so we have left such simulations out of this paper.

[8] The survey was part of a three-wave panel, the first two waves having been conducted in 1997-98 (e.g., in Conley and Udry [2010a]) and 2004 [Vanderpuye-Orgle and Barrett, 2009]. Slightly more than half of the 70 households were part of the initial 1997-98 sample, and the rest were recruited in January 2009 using stratified random sampling by the age of the household head: 18-29, 30-64, 64+. the shares of households whose head was in each of these age categories corresponded to the community's population shares. In the original sample, and in the 2009 re-sampling, we selected only from the pool of households headed by a resident married couple. However, we retained households from the 1997-98 sample even if only one of the spouses remained.

[9] Some men in the sample have two or three wives, all of whom were included. However, for the sake of simplicity we refer to households throughout the text as having two spouses.

are between 7 and 12 sampled 'single-headed households' in each community. In total the sample used in our study includes 606 individuals comprising 325 households in each of the four communities.

Survey. Each respondent was interviewed five times during 2009, once every two months between February and November.[10] Each survey round took approximately 3 weeks to complete, with the two survey teams each alternating between two villages. The survey covered a wide range of subjects including personal income, farming and non-farm business activities, gifts, transfers and loans, and household consumption expenditures. Each round, both the husband and wife heading each household were interviewed separately on all of these topics. Our data set is assembled mainly using information contained in the expenditure, gift and social network modules of the survey.

The expenditure module asked detailed information on the quantities and values purchased of a long list of items with broad categories including home produced food consumption, purchased food consumption, school-related expenditures (fees and complementary goods such as uniforms), medical expenditures (medicine and health fees), among others. Referring to the month prior to the interview, we asked each spouse about his or her own expenditures, those of their partner, and about expenditures of the household as a whole. Appendix table B1 collects summary statistics. Of note in this table is the observation that there is within-household specialization in food expenditures: household heads (mostly males) are more responsible for procuring food produced on the household's farm while the spouse (mostly females) are responsible for purchasing food to supplement home-produced food. Given that the household head and spouse seem to coordinate around total household food consumption, we aggregate variables at the household level.[11]

[10] For details regarding interview timing and survey instruments, see Walker [2011].

[11] For food expenditures, this involves summing the household head and spouse's "own food" consumption. Each individual provides his or her own list of gifts given/received and is not asked to report spouse's gift

In the gifts module, respondents were asked to report any gifts (in cash or in kind) given and received during the past two months, obtaining information on the counterparty's location and relationship to the respondent. The value of the gift given and an estimated value for in-kind gifts were also recorded. We pool monetary and in-kind gifts into a single measure and drop incidents within-household transfers — i.e., gifts transferred to one's spouse. Since we are primarily interested in gifts received from others who are potential winners of lottery prizes, we drop observations of gifts received from others who do not reside within the village.

After selecting the sample but before collecting baseline data a detailed survey of respondents' social contacts was conducted. Each respondent was asked in turn (and in random order) about every other respondent in the sample from his or her community. More specifically, the social network module of the survey asked whether they knew the person, by name or personally, how often they saw them, whether they were related, what they perceived the strength of the friendship to be, whether they had ever given or received a gift to or from the person, and whether they would trust the person to look after a valuable item for them. Due to the nature of the data, we can confirm the bi-directional nature of reciprocal gift-networks. We do this by merging individual i's response regarding j's gift-giving behavior with individual j's response of i's gift-giving behavior. We establish a reciprocal gift-link between any two individuals when both state that they have ever received and given gifts to the other individual. This substantially reduces any concerns regarding the measurement error of the network. We consider that two households are linked to each other in a reciprocal gift-giving relationship if at least one pair of the potential combinations engages in mutual gift-giving. For example, there are four total combinations between household A and

information, so household aggregation is a straightforward sum of these lists for gift-related variables. See Castilla and Walker [2013] for a study analyzing how information asymmetry influences spending decisions within the household using the same data.

B when both households have one male (M) and female (F) head/spouse: AM-BM, AM-BF, AF-BM, AF-BF. If a reciprocal gift-giving links exists between at least one of these pairs, then we state that household A and B have a reciprocal gift-giving relationship. Otherwise, no such link exists. Household-aggregated measures that form the basis of our analysis are represented in table 3.1. On average, each household has roughly five members and has reciprocal gift-giving relations with 11.5 other households. Roughly 13% of the households in do not have in reciprocal gift-giving links with any other household in the sample. Across the five rounds of data, households give and receive 1.58 and 0.58 gifts respectively to any other household over the course of two months. The average total value of the gifts given (received) is 20.02 (12.58) GH¢. Household per-capita food consumption is reported in the third panel of table 3.1. The total household per-capita food consumption in our sample is 26.64 GH¢, 68% of which is purchased food.[12]

Experimental Data. The first round of the survey was designed as a baseline, therefore no lottery took place in that round. One week before each subsequent round we visited each village to distribute prizes to selected respondents. Twenty prizes were allocated in each community, in each of the four lottery rounds, so that in all 320 prizes were given. Over the four lotteries, approximately 42 percent of individuals and 62 percent of households won at least one prize. Ten of the prizes were divisible in the form of cash, whereas the other ten were in the form of livestock. Of these, five each were allocated publicly by lottery, and the other five (identical in type) were allocated in private, by lucky dip. The values of the prizes varied from GH¢10 to GH¢70 as described in figure 3.5.[13] The prizes were of a substantial

[12]Seasonal conditions account for inter-temporal variation in the amount/value of purchased food in the household.

[13]In this paper, we are primarily interested in transfers of divisible windfall gains, thus we focus our attention on cash lottery winnings. The livestock were purchased in Accra on the morning of the lottery and transported to the community. The value of the price differed according to the type of livestock: Chickens (10¢), two chickens (20¢), small goat (35¢), medium goat (50¢), and large goat (70¢). Different households may face different transaction costs, so the value of livestock, as opposed to cash, is heterogeneous across households, which further complicates the use of livestock in the analysis. Additionally, in this study context,

size - the largest prize is equivalent to a month's worth of food consumption for an average household with five members. In aggregate, each community received GH¢370 of cash in each round to use however they would like.

The lotteries took place one week before the commencement of the survey interviews. We took great care to make clear to participants that the allocation of prizes was random, and that each individual had an equal chance of winning in each round. A village meeting was held in a central area of the community, and all respondents were invited to attend. A small amount of free food and drink was provided as an incentive to come. Attendance at the meetings was generally around 100 people; roughly half of the respondents appeared for each meeting.[14] There were usually a number of non-respondents at these meetings as well, including many children. At each gathering we thanked the participants for their continued support. We explained that respondents had a chance to win one of 20 prizes that day, framing the prizes as a gratuity for their participation in the survey.[15] We then proceeded to draw winners for the ten public prizes (without replacement) from a bucket containing the names of the survey respondents. A village member not in the sample was chosen by the villagers to do the draw, in order to emphasize that the outcomes were random. Each winner was announced to the group, and asked to come forward to receive their prize. The prizes were announced and displayed clearly before being awarded. Respondents who were absent at the time of drawing were called to pick up their prize in person, if possible. Unclaimed prizes were delivered in person to the winner after the lottery. After the public lottery

it is more difficult to 'privately' grant lottery winners a large goat than it is to privately grant them the same amount in cash.

[14] Around 125 of the 150 respondents in each community appeared for the privately revealed lottery, some of them arriving before or after the public meeting.

[15] Respondents signed an informed consent form at the start of the survey, explaining how they would be remunerated for their participation in the survey. Entry in the lottery and lucky dip was part of this remuneration. In addition to the chance of winning a prize, each respondent was given a small amount of cash for their participation, which varied across rounds. This gift was used as an endowment in a public goods experiment as part of a separate study.

prizes were distributed, we conducted a second round in private. Respondents were asked to identify themselves to a survey worker, who took their thumbprint or signature and issued them with a ticket displaying their name and identification number. They then waited to enter a closed school room, one at a time, where an enumerator invited them to draw a bottle cap without replacement from a bag. There was one bottle cap for each of the N respondents in the community. Of these, N - 10 were non winning tokens (red colored), and ten were winning tokens, marked distinctively to indicate one of the ten prizes listed in figure 3.5.[16] Those who drew winning tokens were informed immediately that they had won a prize, which was identified to them, and were told that they did not have to tell anyone else that they had won. We emphasized that the survey team would not divulge the identities of winners who won in private. Cash prizes were given to the winners immediately and winners often hid their prizes in their clothes before leaving the room. The survey interviews in each round commenced one week after the lottery, deliberately delayed to allow winners to receive their prize and do something with it. The interviews took place in no specified order throughout the following three weeks, so that some winners were interviewed a week after receiving their prize, and others up to four weeks afterward.

Appendix table B3 presents balance tests conducted on variables collected at baseline according to whether one member of the household won any of the public or private lottery at any point over the course of the year. 119 of the households in the study are thus in our "treatment" group while the remaining 190 did not win a cash prize. We also separate the test according the households that won the privately revealed vs. publicly revealed lottery. The table suggests that randomization was successful — of the 21 tests along which we seek

[16]Care was taken to shuffle the bottle caps after each draw, and to prevent respondents from seeing into the bag. If a respondent drew more than one bottle cap, those caps were shuffled and the respondent was asked to blindly select one of them. Respondents were shown a sheet relating the tokens to the prizes (See Walker [2011]). At the conclusion of the day, tokens that had not been drawn were counted and the remaining prizes allocated randomly among the non-attending respondents using a computer. There were usually 25-30 non-attendees and less than three prizes remaining.

to reject balance, one is significant at the 5% level and another is significant at the 10% level. For the others, balance cannot be rejected at the 10% level.

To calculate gift-network lottery winnings, we simply take the average cash winnings (private vs. public) of each household's gift-network. In other words, for every household i out of N, private (replaceable with public) network lottery winnings are

$$\overline{\text{Private}}_{it} = \sum_{j=1}^{N} \frac{\text{Private}_j \times \mathbb{1}(g_{ij} == 1)}{\sum_{j=1}^{N} \mathbb{1}(g_{ij} == 1)},$$

where $g_{ij} = 1$ if there is a reciprocal gift-giving relationship between households i and j (0, otherwise), $\text{Private}_j \in \{0, 10, 20, 35, 50, 70\}$ are the values of cash prizes household j can win and $\mathbb{1}$ represents the indicator function.[17] The bottom two panels of table 3.1 present the average (log) value of own and network cash winnings and show that average prize winnings roughly represent the expected value of the cash prize of all households in the village sample.

3.4 Empirical Investigation

The unique features of our experimental design allows us to bring the model predictions to the data in a straightforward manner. Let y_{it} be the outcome of interest: either the amount of round t gifts distributed or the number of round t gifts distributed by household i. The shutdown hypothesis (Prediction 1 in Section 3.2) can be investigated using the following regression:

$$\begin{aligned} y_{it} = \alpha &+ \beta_v \text{Private}_{it} + \beta_b \text{Public}_{it} \\ &+ \beta_{vg} \text{Private}_{it} \times \text{Net-size}_i + \beta_{bg} \text{Public}_{it} \times \text{Net-size}_i \\ &+ \text{hh}_i + \text{r}_t + \epsilon_{it}, \end{aligned} \tag{3.14}$$

[17] In one round, both the household head and spouse within the same household won the lowest of two public lotteries. Hence, for this household, the prize winnings amounted to 30.

where β_v captures the extent to which round t gift-behavior is influenced by round t privately revealed lottery winnings and β_b captures the influence of publicly revealed lottery winnings. Net-size$_i$ is household i's reciprocal gift-network size. hh_i captures household fixed effects and r_t captures round fixed effects. Importantly, notice that household fixed-effects control for all time-constant household factors including the size of its gift-network. Given the distribution of the outcome variables, the specific estimator will place restrictions on the error term, ϵ_{it}. Specifically, when the outcome variable is the (log) amount of gifts given, we use the tobit estimator where we integrate out censored observations equal to zero. The number of gifts given follows a poisson distribution, so we use a poisson estimator to estimate the coefficients of interest under this dependent variable. Predictions 2 and 3, that do not depend on heterogeneity in network size, can simply be tested by setting the interaction terms equal to zero.

An empirical investigation of the model implication in terms of consumption (Prediction 5, Section 3.2) requests instead to relate household i's consumption behavior against the average lottery winnings of i's gift network — i.e.,the average network treatment effect on consumption (defined in Section 3.3). Thus, we estimate the following equation:

$$y_{it} = \alpha + \beta_v \text{Private}_{it} + \beta_b \text{Public}_{it} + \beta_{vn} \overline{\text{Private}}_{it} + \beta_{bn} \overline{\text{Public}}_{it} + \text{hh}_i + \text{r}_t + \epsilon_{it}, \tag{3.15}$$

where y_{it} is log per-capita household food consumption. We do not expect food consumption to be an increasing linear function in network lottery winnings. However, we do expect that households with lower levels of period-specific food-consumption will receive more support from their network. Therefore, we opt to use a quantile regression estimator to examine effects at different locations along the consumption distribution. Table 3.2 summarizes how coefficients in each of the estimation equations link to predictions from our theoretical model.

Table 3.3 contains the estimation results of model 3.14 with three different outcome variables, with and without interaction terms. The negative coefficient in the fourth row (β_{bg}) of columns 4-6 indicates that individuals winning the public lottery are associated with lower levels of transfers the larger is their gift network size. This is in line with the shut-down hypothesis predicted by our model (prediction 1). Notice that in column 3, the first row coefficient (β_v) is larger than the second row coefficient (β_b) — this confirms the hypothesis that each individual gift is, on average, larger for individuals winning the private lottery (prediction 2). Notice the difference in the second row in columns 2 and 5. In column 5, β_b is positive and large but is insignificant from zero in column 2. This indicates that without including the interaction effect, we underestimate the number of gifts given for someone with a relatively small gift-network after winning the public lottery. This suggests that prediction 3 is confirmed. Furthermore, the second row in columns 1 and 4 show a similar story — furthermore, β_b is larger than β_v in column (4), which is consistent with the pattern we observe in figure B1 (prediction 4). Figure 3.7 provides a non-parametric test of prediction 4 — it is consistent with figure B1 generated by model simulations. Finally, figure 3.6 estimates equation 3.14 as a fourth-order polynomial (take powers 0-4 on the interaction coefficient and sum them together) and shows a shut-down network size of roughly 15 individuals in the mutual gift-giving network (taking point estimates as given).

Turning to the model implications in terms of consumption, we depict graphically the results of the quantile estimation of equation (3.15) in Figure 3.8. We use observations from the first three rounds of data — the hungry season in Ghana when unlucky households are most likely to require help from others. The lower the per-capita food consumption, the more likely one is to increase consumption when their friends win the private lottery winning — the coefficient on private average network lottery winnings is positive and greater than zero for analyzed quantiles less than the 50th percentile. The same cannot be said about the public lottery winnings of one's gift network. Here, the coefficient is only positive for households whose per-capita food consumption falls below the 10th percentile. Furthermore, consumption increases by a smaller margin at the lowest percentiles when gift network members win public relative to private lotteries. These results are all in line with prediction 5 and likely flow from the fact that households who win publicly revealed lotteries are subject to social taxation and are unable to assist connected households who exhibit great need.

3.5 Robustness and Extentions

The extremely detailed micro-structure of our data offers an alternative strategy to test the model predictions and look further into underlying mechanisms. Let g_{ij} be a dyadic variable taking value 1 if household i has an established reciprocal gift-giving link with household j, equation 3.14 takes the following form:

$$\begin{aligned} y_{ijtv} = \alpha &+ \beta_v \text{Private}_{it} + \beta_b \text{Public}_{it} \\ &+ \beta_{vg} \text{Private}_{it} \times \text{Net-size}_i + \beta_{bg} \text{Public}_{it} \times \text{Net-size}_i \\ &+ \gamma \text{Net-size}_i + \text{village}_v + \text{r}_t + \epsilon_{ijt} \end{aligned} \tag{3.16}$$

where the outcome variable measures (log) gifts amounts and numbers given from i to j and village fixed effects are included (instead of household fixed effects). Although transfers among dyads within our sample constitute a small share of total transfers reported in the survey's gift-module, this model specification provides a robustness check and, more importantly, allows us to examine the extent to which households target each other for gifts. Further, we can differentiate between dyads who have a mutual gift-giving relationships and those that do not.

Recall, altruistic preferences imply that household i's marginal utility is an increasing function of the relative suffering of household j — in other words, the lower household j's consumption levels relative to i, household i is more incentivized to transfer resources to household j under altruistic preferences. To examine this prediction in our data, we can estimate the following equation via dyadic analysis:

$$\begin{aligned}y_{ijtv} = \alpha &+ \beta_v \text{Private}_{it} + \beta_b \text{Public}_{it} \\ &+ \beta_{v\chi} \text{Private}_{it} \times (\hat{\chi}_i - \hat{\chi}_j) + \beta_{b\chi} \text{Public}_{it} \times (\hat{\chi}_i - \hat{\chi}_j) \\ &+ \gamma(\hat{\chi}_i - \hat{\chi}_j) + \text{village}_v + \text{r}_t + \epsilon_{ijt}\end{aligned} \tag{3.17}$$

where we have replaced the "Net-size$_i$" interaction term with the difference in household i and j's food shocks, $\hat{\chi}_i - \hat{\chi}_j$. The "more positive" i's food consumption shock is relative to j's, the higher the difference. If i holds altruistic preferences over j, then $\beta_{\{v,b\}\chi}$ will be positive. We measure food shocks in the following way. Given the panel nature of our data, we measure deviations from round-adjusted average household per-capita food consumption by recovering the OLS residual error term from the equation:

$$\text{Per-Capita Food}_{it} = hh_i + r_t + \chi_{it}$$

where hh_i and r_t are respectively household and round fixed effects. The resulting variable, $\hat{\chi}$ measures household-round specific shocks to per-capita food consumption.

Table 3.4 and 3.5 reports the OLS estimation results of model 3.16 without and with interaction terms, respectively. Each of these tables splits the sample into those dyads who have a mutual gift-giving relationships and those that do not. Overall, evidence is consistent with the model and suggests that private lottery winnings are transferred to individuals who are already in one's gift-giving network. Public lottery winnings are more likely to go to individuals who are not in one's mutual gift-giving network, suggesting that individuals outside of this network will solicit the lottery winner for help. The shut-down hypothesis is again confirmed, although standard errors are large. More specifically, column 2 of table 3.6 shows that while all individuals in one's network receive more gifts when individual i

wins the privately revealed lottery, the largest gifts are reserved for those households j whose food-shocks are largest. In other words, household i gives more to households whose realized food consumption is much lower than household i's realized food consumption. This same pattern does not take place when household i wins the publicly revealed lottery. Instead, when household i wins a publicly revealed lottery, he gives to households who are not in its gift network only when they experience a negative food shock relative to household i. This is totally in line with model prediction 5. Table B6 estimates a triple-interaction that pools all observations and shows evidence consistent with table 3.6.

We conclude this section with an exploration of the channels motivating solidarity network. In particular, we would like to investigate whether we find evidence consistent with altruism being an important driver, besides insurance. If social solidarity networks indeed smooth members' consumption by distributing income shocks across the network, the familiar prediction, following Townsend [1994], is that the inter-temporal change in one member's consumption should track one-for-one the average consumption change over the same period within the rest of one's network. Within our model, the testable prediction is the null that the coefficient relating a survey respondent's period-on-period change in log consumption to the contemporaneous change in network average consumption equals one. Within our model, across the full social solidarity network we expect to reject the null in favor of the one-sided alternate hypothesis that the coefficient is less than one but also to reject the null that change in consumption is uncorrelated, in favor of the one-sided alternate hypothesis that they are positively correlated. This occurs because of the shut down hypothesis and because private winnings will not get shared with networks members who do not exhibit great material need.

Table 3.7 reports results of those hypothesis tests. We show that limited risk pooling occurs within the full network. The point estimate of 0.23 is statistically significantly greater than 0 only at the 10 percent level and one can easily reject the null that it equals 1.00. Meanwhile, the respondent's own winnings, whether private or public, and the average winnings within one's network are statistically insignificantly related to a respondent's consumption volatility once one controls for consumption volatility within one's network, consistent with the altruism in networks model of Bourlés et al. [2017]. From this result, we can conclude that there are multifaceted drivers of gift-giving in this gift-network that may include limited degrees of risk pooling, but likely involve solidarity among network ties. In summary, our evidence points toward th efact that it is hard to argue that the solidarity network is motivated mainly by insurance. Combined with the significant giving from private winnings, it certainly appears that altruism and taxation are more compelling explanations. Insurance may play a role, but it hardly seems a primary role.

3.6 Conclusion

We analyse altruistic preferences in networks by examining a model of risk sharing under imperfect commitment where the impurely altruistic gains to giving to others diminish with the number of transfers one makes. Giving is costly, and stochastic income has both publicly observable and unobservable components. Contrary to the canonical informal insurance model, in which bigger networks and observable income are preferable, our model predicts that unobservable income shocks may facilitate altruistic giving that better targets the least well off within one's network and that too large a network can overwhelm even an altruistic agent to cease giving. Full risk-pooling is maintained within the network that remains so long as an agent does not exist the arrangement. We take these predictions to a unique data set from southern Ghana. We couple observations of gift-giving networks with experimental cash windfall gains - randomized between private and publicly observable payouts - repeated every other month for a year to analyze transfer flows among households. We find four striking results. First, on average, more gifts are given out of private cash winnings than public cash winnings, signaling that altruistic preferences - not just self-interested behavior within an endogenously enforceable insurance scheme - must be a significant driver of inter-household transfers. Second, winners of privately revealed prizes target giving to the neediest households within their networks, indicating greater social welfare gains from altruistic transfers than from insurance transfers. Third, winners of publicly revealed cash prizes do not make transfers when they have large networks; they break the informal contract due to network size. Fourth, conditional on transfers flowing within one's network, we cannot reject the null of full risk pooling. These results highlight the limits to social networks as channels for managing income shocks as well as the trade-offs inherent to transparency in transfer programs. Although observability of income is essential in informal insurance arrangements among purely self-interested agents, observability may impede altruistic agents' ability to focus their giving on the most needy as they are compelled to respond to demands for assistance from the less needy within their network.

Tables

Table 3.1: Household Summary Statistics

	N	Mean	Sd	5 p-tile	95 p-tile
Fixed Over Time:					
HH size	309	4.94	2.19	2	8
N of HH in Solidarity Network	309	11.56	10.11	0	32
Gifts (last 2 months, GH¢):					
N Gifts Given	1,525	1.60	2.16	0	6
N Gifts Received	1,525	1.45	1.95	0	5
Total Value of all Gifts Given	879	26.77	88.94	1	90
Total Value of all Gifts Received	893	46.38	130.77	1.50	158
Food Consumption (last month, GH¢):					
PC Food Consumption	1,525	26.64	21.70	5.05	65.10
PC Purchased Food	1,525	18.12	19.14	0	48.93
PC Home-produced Food	1,525	8.51	8.53	0	23.45
Own Lottery Winnings (GH¢):					
Cash - Private	1,525	1.84	9.42	0	0
Cash - Public	1,525	1.87	9.55	0	0
Solidarity Network Average Lottery Winnings (GH¢):					
Solidarity Network Cash - Private	1,525	1.81	4.52	0	8.33
Solidarity Network Cash - Public	1,525	1.74	4.29	0	8.33

Gift Network data missing for a subset of observations. N of gifts given/received equal zero if none given/received. Value of gifts contingent on having received at least one. Household food consumption (total) sums the head of households and spouse's response. Solidarity network lottery winnings multiply the vector of lottery winners by the row-normalized network adjacency matrix (result is average networks' lottery winnings). Network values represent log transformations of original winnings/averages.

Table 3.2: Linking Empirical Analysis to Theoretical Predictions

Equation	Predictions				
	1 Shut-Down	2 Average Gift Value	3 Gift Number	4 Total Value	5 Consumption*
3.14|Net-size = 0		$\beta_v > \beta_b$	$\beta_b = \beta_v$	$\beta_b = \beta_v$	
3.14	$\beta_b > 0, \quad \beta_{bg} < 0$		$\beta_b > \beta_v$	$\beta_b > \beta_v$	
3.15					Quantile Regression**

Notes: * Tests referring to prediction 5 suggest that those households who have lower levels of food consumption relative to network contacts who win the lottery will be more likely to receive transfers and will receive higher values per transfers. ** Indicates coefficient on β_{vn} should be larger at lower quantiles.

Table 3.3: Prize Winnings Influence Gift-Giving

	No Interaction			Shut-down Hypothesis		
Dep. Var.: Gifts-Given	Value	Number	$\frac{\text{Value}}{\text{Number}}$	Value	Number	$\frac{\text{Value}}{\text{Number}}$
Private Cash Winnings	0.010*	0.017**	0.007**	0.010*	0.016**	0.007*
	(0.005)	(0.007)	(0.004)	(0.005)	(0.007)	(0.004)
Public Cash Winnings	0.002	0.005	-0.001	0.012	0.026***	0.004
	(0.005)	(0.007)	(0.003)	(0.007)	(0.010)	(0.005)
Public Cash Winnings × N Mutual Gifts				-0.001*	-0.002***	-0.001
				(0.001)	(0.001)	(0.000)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1602	1602	1602	1602	1602	1602

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Dependent Variable equals log value of gifts given in columns 1 and 4, number of gifts given in column 2 and 5, and log value per gift ($\frac{\text{log(Total Value)}}{\text{Total Number}}$) in columns 3 and 6. Household and Round Fixed Effects Included in Every Specification. Coefficients estimated using Tobit estimator with a lower bound of zero (no upper bound). Log transformation of variables adds one to original value so that zero values are preserved under log transformation.

Table 3.4: Dyadic Regressions

	Mutual		All Other Sample Links	
	Log(Amount$_{ijt}$)	Number$_{ijt}$	Log(Amount$_{ijt}$)	Number$_{ijt}$
Lottery-Private$_{it}$	0.322*	0.296***	-0.462	-0.241*
	(0.190)	(0.081)	(0.289)	(0.145)
Lottery-Public$_{it}$	0.168	-0.013	0.136	0.086
	(0.185)	(0.095)	(0.202)	(0.101)
Village FE	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes
N	19330	19308	114645	111453

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable in even columns equals amount of actual gift given from i to j in any given round t; Odd columns equals number of gifts. 'Network Size$_i$' indicates household i's gift-network size (any type of gift-relation). Odd columns are tobits with lower bound of zero. Even columns are poisson regressions. Columns 1-2 only include links (i and j) with mutual gift-relations at baseline (178 actual gifts given during the 5 rounds). Columns 3-4 include all oher links (180 actual gifts given).

Table 3.5: Dyadic Regressions - Shutdown

	Mutual		All Other Sample Links	
	Log(Amount$_{ijt}$)	Number$_{ijt}$	Log(Amount$_{ijt}$)	Number$_{ijt}$
Network Size$_i$	-0.017	-0.010	0.052	0.023
	(0.023)	(0.013)	(0.036)	(0.015)
Lottery-Private$_{it}$	0.607**	0.330***	0.239	0.083
	(0.301)	(0.125)	(0.340)	(0.156)
Lottery-Public$_{it}$	0.495	0.131	0.502**	0.298**
	(0.365)	(0.182)	(0.247)	(0.125)
Lottery-Private$_{it}$ $\times$ Network Size$_i$	-0.016	-0.002	-0.112***	-0.052***
	(0.014)	(0.006)	(0.043)	(0.019)
Lottery-Public$_{it}$ $\times$ Network Size$_i$	-0.019	-0.009	-0.040*	-0.026**
	(0.020)	(0.011)	(0.023)	(0.013)
Village FE	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes
N	19330	19330	114645	114645

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable in even columns equals amount of actual gift given from i to j in any given round t; Odd columns equals number of gifts. 'Network Size$_i$' indicates household i's gift-network size (any type of gift-relation). Odd columns are tobits with lower bound of zero. Even columns are poisson regressions. Columns 1-2 only include links (i and j) with mutual gift-relations at baseline (178 actual gifts given during the 5 rounds). Columns 3-4 include all oher links (180 actual gifts given).

Table 3.6: Dyadic Regressions - Food Shocks

	Mutual Gift		All Other Sample Links	
	Log(Amount$_{ijt}$)	Number$_{ijt}$	Log(Amount$_{ijt}$)	Number$_{ijt}$
Lottery-Private$_{it}$	0.259	0.295***	-0.560*	-0.285**
	(0.205)	(0.092)	(0.302)	(0.144)
Lottery-Public$_{it}$	0.118	-0.038	0.007	0.032
	(0.190)	(0.096)	(0.229)	(0.113)
Food-Shock$_{ijt}$	-0.157	-0.093	-0.061	-0.039
	(0.210)	(0.101)	(0.282)	(0.136)
Lottery-Private$_{it}$ × Food-Shock$_{ijt}$	0.462***	0.118*	-0.574*	-0.256*
	(0.169)	(0.064)	(0.322)	(0.132)
Lottery-Public$_{it}$ × Food-Shock$_{ijt}$	-0.265	-0.110	0.618*	0.254*
	(0.304)	(0.153)	(0.336)	(0.140)
Village FE	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes
N	18374	18374	92347	92347

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable in even columns equals amount of actual gift given from i to j in any given round t; Odd columns equals number of gifts. 'Food-Shock$_{ijt}$' indicates the difference between i and j estimated food consumption residual ($\hat{\chi}_i - \hat{\chi}_j$ — household and round fixed effects). Odd columns are tobits with lower bound of zero. Even columns are poisson regressions. Columns 1-2 only include links (i and j) with mutual gift-relations at baseline (169 actual gifts given during the 5 rounds). Columns 3-4 include all oher links in the sample (156 actual gifts given).

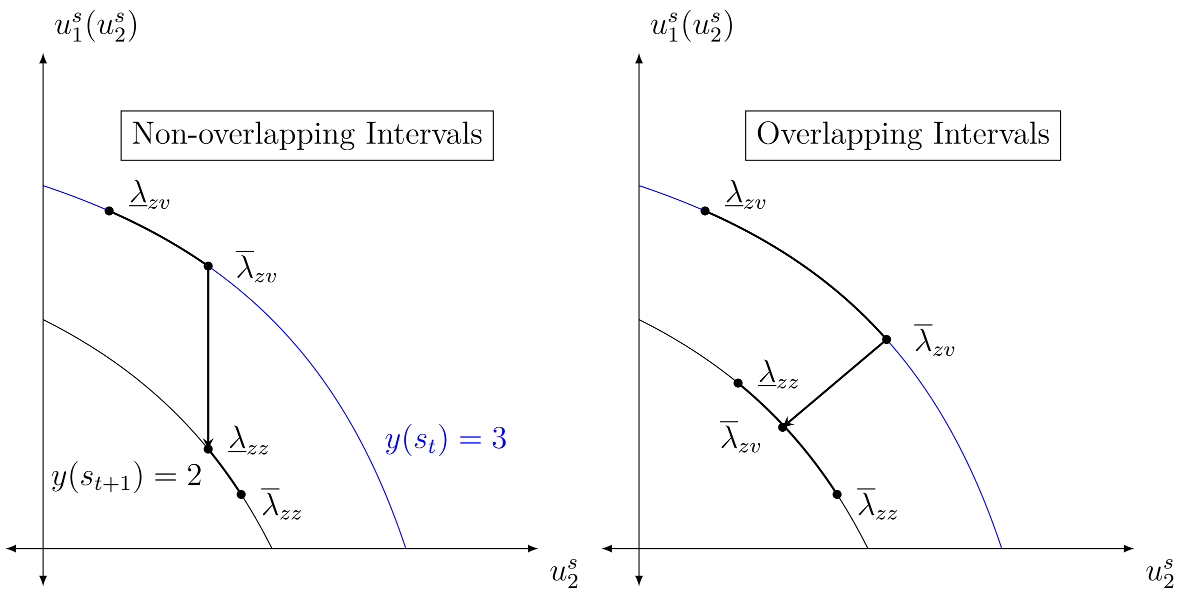
Table 3.7: Tests of Full Risk-Sharing

	$\Delta\log(\text{food})_{ivt}$
$\Delta\overline{\log(\text{food}\vert\text{NET})}_{ivt}$	0.232*
	(0.138)
Private Cash Winnings	0.062
	(0.057)
$\overline{\text{Private Cash Network Winnings}}$	0.016
	(0.046)
Public Cash Winnings	-0.038
	(0.035)
$\overline{\text{Public Cash Network Winnings}}$	-0.018
	(0.039)
HH FE	Yes
Round FE	Yes
N	1279

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent Variable equals first difference of log per-capita household food consumption. Coefficients represent OLS estimators. Variables with line above the variable name indicate household i network's average for each variable.

Figures

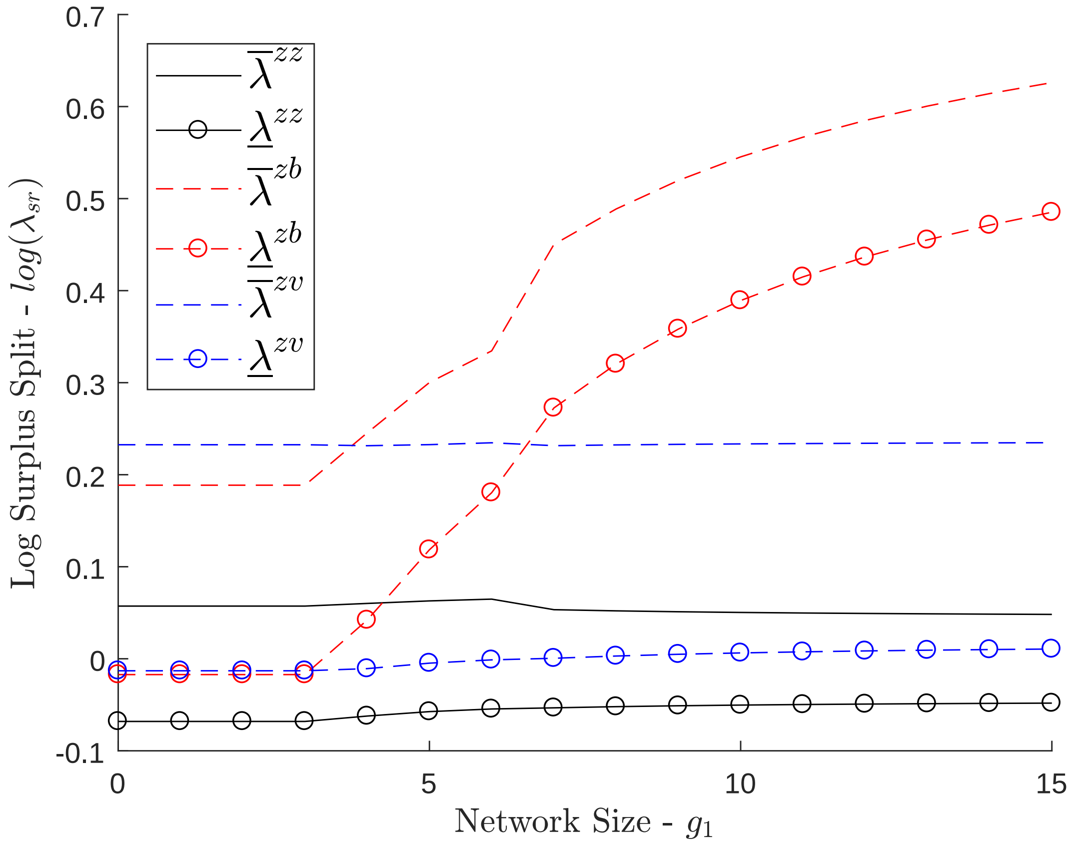
Contract Intuition



Note: This figure shows how contract intervals relate to the pareto frontier when 1) intervals overlap and 2) when they do not. Values along the x-axis represent household 2's single-period utility and y-axis represents household 1's single-period utility. In state $s_t = zv$, household 1 receives an income of $y_1(zv) = 2$ and household 2 receives an income of $y_2(zv) = 1$ (aggregate income, $y(zv)$, equals 3). In state $s_{t+1} = zz$, both households receive an income of 1 ($y(zz) = 2$). We assume that in period t contracts are such that household 2 receives the entire discounted utility surplus ($\lambda(h_t) = \overline{\lambda}_{zv}$). In period $t+1$, the resulting division of surplus depends on whether or not the contract intervals overlap. When there is no overlap (left-hand side), $\lambda(h_{t+1}) = \underline{\lambda}_{zz}$. When there is overlap, $\lambda(h_{t+1}) = \lambda(h_t) = \overline{\lambda}_{zv}$. Overlapping contracts allow for higher degrees of consumption smoothing over periods.

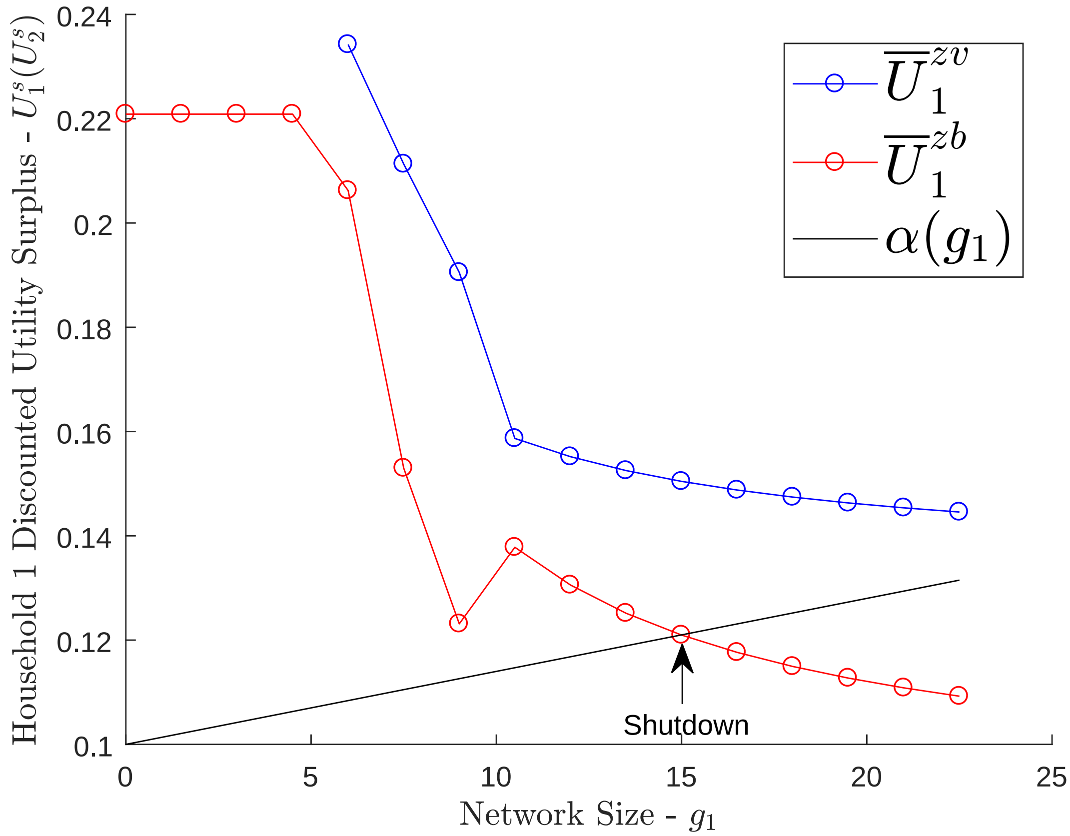
FIGURE 3.1: figure

Figure 3.2: Contract Intervals



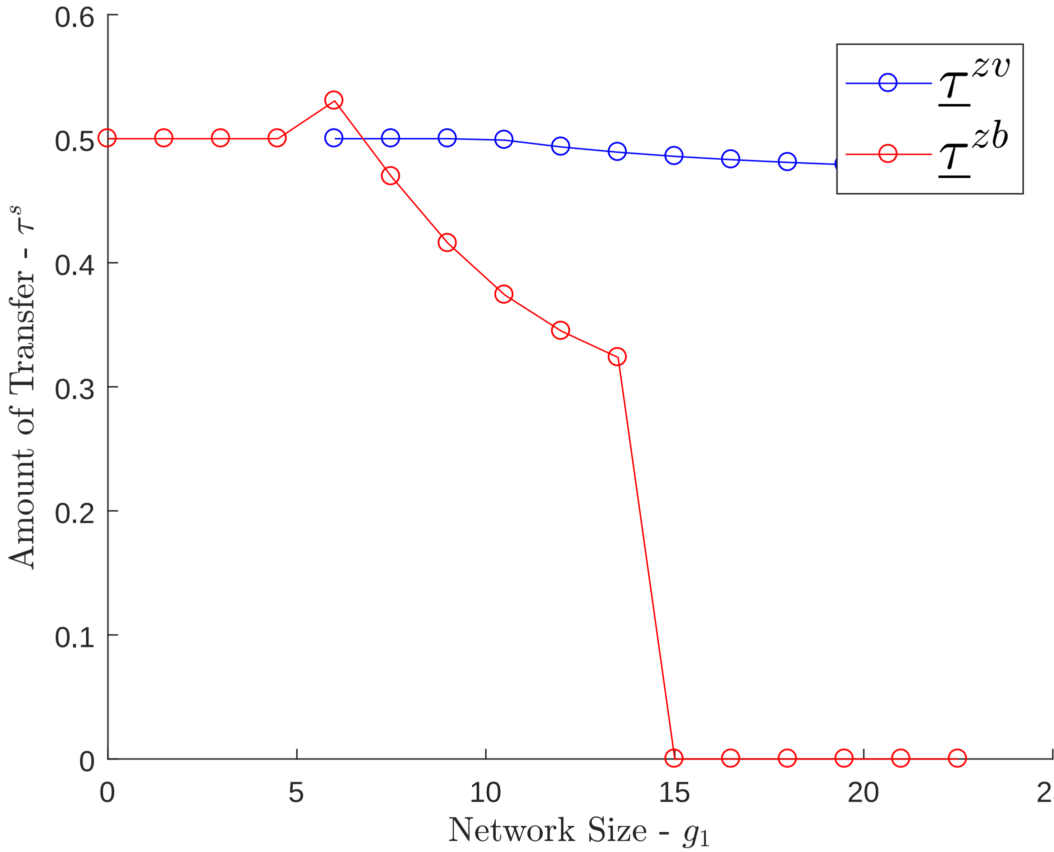
Note: Contract interval solutions as a function of network size with log utility (i.e., $u_1() = u_2() = ln()$. Logged values of λ on the y-axis and network size on x-axis. Contract intervals in state zb increase when $g_1 > 3$ and no longer overlaps with zz when $g_1 > 4$. Furthermore, it is non-overlapping with zv when $g_1 > 6$. The first-best contract (stationary share of aggregate output) is only available when network size is less than three.

FIGURE 3.3: Discounted Lifetime Expected Utility



Note: Discounted lifetime expected utility for household 1 when the initial state iz zv vs. zb and when household 1 takes all available surplus from the transfer arrangement (hence, the underline in $\underline{U}_1^s$). Utility values are universally smaller in state zb and decrease at faster rates than state zv throughout. Utility spikes for a single period ($10 < g_1 < 11$), which coincides with the zb contract interval no longer overlapping with zv (see figure 3.2). The cost of maintaining each network tie, arbitrarily set to $\alpha(g_1) = .1 + .001g_1^{1.2}$ is increasing in network size and intersects with $\overline{U}_1^{zb}$ at a threshold of $g_1 = 15$. Beyond this point, household 1 shuts down all gift transactions when it reaches the zb state. We plot $\overline{U}_1^{zb}$ without the possibility of shutdown; however, utility is $\overline{U}_1^{zb} = 0$ whenever $g_1 > 15$.

FIGURE 3.4: Amount of Transfer by Network Size



Note: This figure represents transfer amounts $\underline{\tau}^s$ from household 1 to household 2 when household 2 takes the entire share of the surplus (U_1^s is set to zero) and when household 1 wins a cash prize. Thus, it also represents the average transfer amount from household 1 to any other household in its gift network when it wins a cash prize. The average transfer amount is generally smaller when household 1 wins the publicly revealed prize (zb) relative to when it wins the privately revealed prize (zv). Transfers are reduced to zero beyond household 1's shutdown point ($g_1 = 15$).

Figure 3.5: Experimental Data: Lottery Payouts

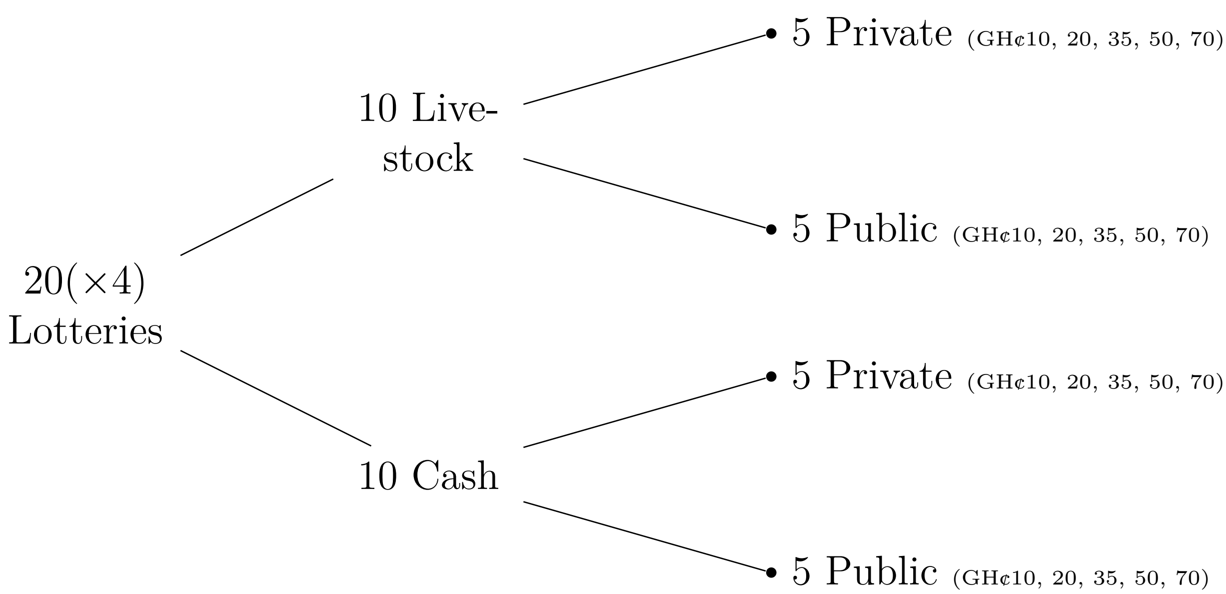
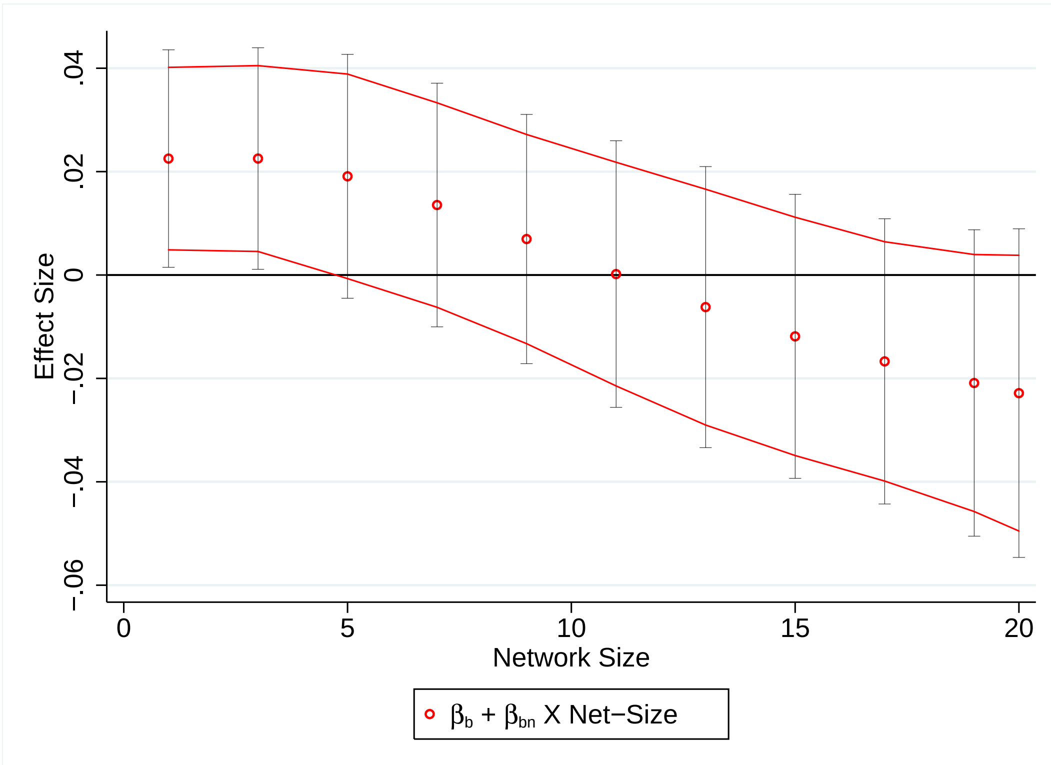
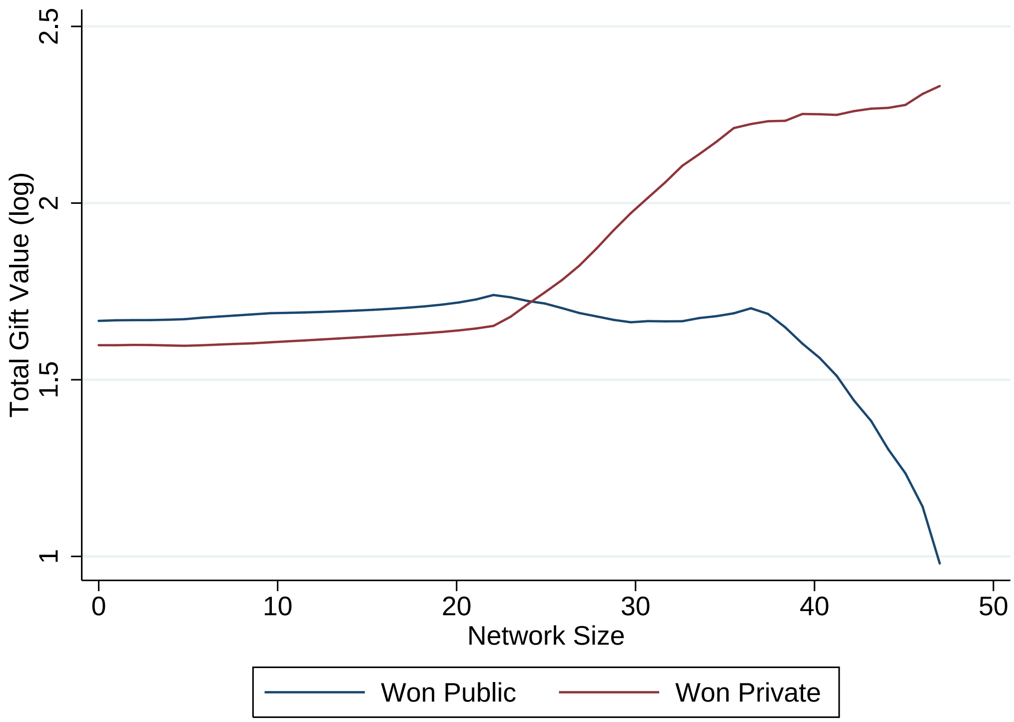


FIGURE 3.6: Shut-down Hypothesis on Number of Gifts Given



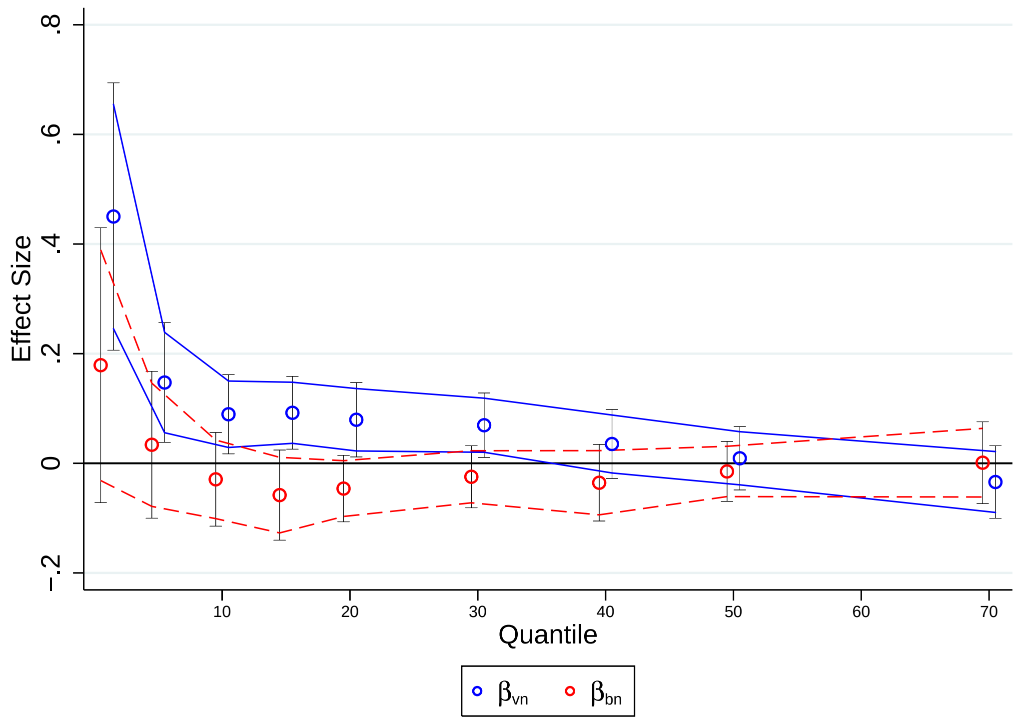
Note: Dependent variable equals number of gifts given. Estimation of equation 3.14 with the inclusion of 2nd, 3rd, and 4th order polynomial interactions on network-size variable. Results indicate that the coefficient is equal to zero when solidarity network consists of 11 households (within-sample).

FIGURE 3.7: Nonparametric Analysis of Shut-down Hypothesis on Total Value of Gifts



Note: Locally smoothed polynomial of total gift-giving as a function of network size. Variable on the Y-axis is total value of gifts given minus household average across rounds. Red-line only includes sample of individuals who won privately revealed lotteries. Blue line only includes sample of individuals who won publicly revealed lotteries. At small network-size values, total gifts given by public lottery winners is slightly higher than private lottery winners. This relationship remains flat and is inverted at a network size of roughly 20 at which point total gifts given by publicly revealed lottery winners starts to decrease — indicating behavior consistent with the shut-down hypothesis.

Figure 3.8: Effects of Network Lottery Winnings on Food Consumption



Note: Figure represents coefficient estimates of quantile regression of equation 3.15 (HH fixed effects replaced by village fixed effects due to dimensionality constraints). Dependent variable equals log per-capita food consumption. Simultaneous quantile regression estimator with 100 bootstrap repetitions. Only first three rounds of data used — these periods coincide with Southern Ghana's hungry season. Blue represents average network treatment effect of privately revealed lottery winnings and red represents publicly revealed lottery winnings. Evaluated at the 1%, 5%, 10%, 15%, 20%, 30%, 40%, 50%, and 70%-tiles. Per-capita food consumption more likely to increase for lowest quantiles following solidarity network's private lottery winnings relative to public lottery winnings.

CHAPTER 4

COMMUNITY DRIVEN DEVELOPMENT SUFFERS FROM HOMOGENEOUS TREATMENT OF COMMUNITIES

4.1 Introduction

The community-driven development (CDD) paradigm — efforts by governments and civil society organizations to incorporate local management and input in implementation of economic development projects — emerged out of obscurity in the 1990's out of a realization that 1) the large social costs of structural adjustment programs needed to be addressed and 2) emergent development projects would benefit from "bottom-up" approaches that harness local communities' capacity for collective action [Mansuri and Rao, 2013].[1] Belief in the value of these approaches was derived, on the one hand, from evidence suggesting that local community knowledge and capacity for self help can overcome state and market failures and, on the other hand, from a normative commitment to the democratization of participation in development processes [Ostrom, 1990, Sen, 2000].

As Ostrom [1990] shows, however, the esteemed localized relationships and institutions that evolve slowly over time to facilitate local collective action are highly complex and subject to nuanced conditions of local social, political and physical environments.[2] This poses a problem when the scale at which NGOs or governments running CDD projects operate (e.g., in hundreds of villages across a region) requires implementing projects that approach beneficiary communities as homogeneous units without regard for local socio-political complexity.

[1] The World Bank alone invested almost $85 billion to local participatory development in the 2000's [Mansuri and Rao, 2013].

[2] It should be noted that Ostrom [1990] is primarily concerned with studying the governance of common-pool resources. The aim of CDD is to advance economic development, which is more often considered in tandem with public investment, or the provision of public goods. The non-rival nature of public resources differentiates CDD endeavors from efforts to govern the commons. What we show in our analysis is that it is likely that local rules applied to governing common resources are likely indiscriminately applied to the governance of "new" local public goods.

Our focus in this paper is to understand whether these homogeneous relationships between CDD organizations and community groups influence the extent to which local capacity for collective action is harnessed. We show that under a commonly implemented relationship scheme, facilitators of CDD programs are more likely to strengthen operations in communities with strong, authoritarian, local leaders at the expense of more cooperative communities with decentralized power relationships among community members — quite contrary to the intentions of many such schemes.

Specifically, we analyze the efforts of an NGO operating in two districts of central Malawi that forms village-level farmer clubs tasked with disseminating knowledge about new agricultural technologies. The NGO invites clubs to participate in managing experimental demonstration plots for the purpose of transferring knowledge of new agricultural technologies to club members — a central policy strategy of many development organizations [Ashraf et al., 2009, Burke, 2014, Duflo et al., 2014]. The NGO employs a facilitator to liaise with the newly formed clubs via the club's self-appointed "Lead Farmer." The resulting arrangement is one in which the extension officer invites the lead farmer to trainings and visits to centrally-located demonstration plots in an attempt to encourage dissemination of new production practices at the club-level. Clubs are simultaneously invited to raise funds to purchase inputs on loan and provide labor to apply these methods on local plots — either collectively owned experimental plots or on their own fields. Together, the project requires a successful interaction on two levels: 1) between the NGO facilitator and club leaders and 2) club-level interactions conducive to collective action.

We collect four sources of rich quantitative and qualitative data to analyze the extent of within-club cooperative capacity alongside club-NGO relationships: contributions during a public goods game played by the clubs, community and household surveys, club-leader surveys, and focus group discussions with club members. By combining measures of cooperation from behavioral games with survey measures of the local context, we can overcome issues of external validity that often plagues the analysis of games alone. From these data, we highlight four novel results: 1) clubs adopt decision-making processes that cohere to village-level decision-making norms, 2) across villages, decision-making norms exist along a spectrum ranging from highly centralized (leader-driven) decision making to highly decentralized (consultation/consensus-driven) decision-making, 3) clubs with decentralized decision-making are more cooperative in public goods games and manifest club-level characteristics indicative of higher capacity for collective action and 4) the NGO is most likely to interact with clubs whose leaders employ centralized decision-making practices. Our conversation with the NGO's extension officers suggest that they find it more practical to interact with leaders of clubs that are "more responsive." Somewhat intuitively, however, the more responsive leaders are those leaders who wield more power in their clubs — importantly, these clubs are less cooperative on average than clubs with decentralized decision-making, which suggests that the NGO's coordination scheme is not capable of harnessing the most cooperative communities' capacity for collective action.

Our paper shows that much of the cooperative potential of local communities is unlikely to be tapped by many current approaches to CDD design. Three recent review articles on CDD approaches to development recognize that CDD projects have led to positive economic returns [Mansuri and Rao, 2013, Wong and Guggenheim, 2018, Casey, 2018]. However, each recommends deeper investigations into the interaction between CDD design and local participation in community decision-making so that we can gain a better understanding of how CDD can facilitate and benefit from the immense capacity for collective action in local communities. Our study opens up this dialogue and suggests deeper consideration of relational approaches between CDD facilitators and the communities they operate in rather than a homogenous approach to each community. This is particularly important if CDD programs seek to circumvent issues around elite capture when programs are decentralized [Platteau and Gaspart, 2003]. Our paper shows that some CDD facilitation models may unintentionally empower local elites because communities with strong leaders are more responsive and "easier to deal with."

4.2 Background and Conceptual Framework

Our objective in this section is to describe both the context of the CDD program we are analyzing and a conceptual framework that articulates the goals of the project. We analyze a program in Malawi's central districts of Kasungu and Dowa implemented by the international NGO, the Clinton Development Initiative (CDI). In Malawi, CDI organizes farmer clubs linked to a CDI-owned "Anchor Farm" with the following objectives in mind (i) to disseminate information from and organize trainings on the "Anchor Farm" on improved agricultural practices, (ii) providing credit to purchase improved seeds and other agricultural inputs that are farmed on club-managed "demonstration plots," and (iii) facilitating access to output markets by allowing clubs access to storehouses for agricultural produce during harvest.

Figure 4.1 adapts a theory of change of CDD projects from White et al. [2018] to describe how CDI expects to influence outcomes through its Anchor Farm Program. CDI employs district-level facilitators who initiate contact with 125 communities in two districts in Malawi via sensitization meetings (each facilitator is responsible for roughly 60 sensitization meetings). All village residents are invited to participate in a meeting where CDI objectives are described. The facilitator describes that he or she will be working with farmer clubs registered by the community and all villagers are invited to register farmer clubs interested in benefiting from CDI trainings and programs. Club sizes are limited to 20 members and CDI requests that at least half the members of the clubs are female.

Once clubs are formed, facilitators ask the clubs to select a lead farmer, chairperson, treasurer, and secretary to liase with. The lead farmers, and typically one other leader per

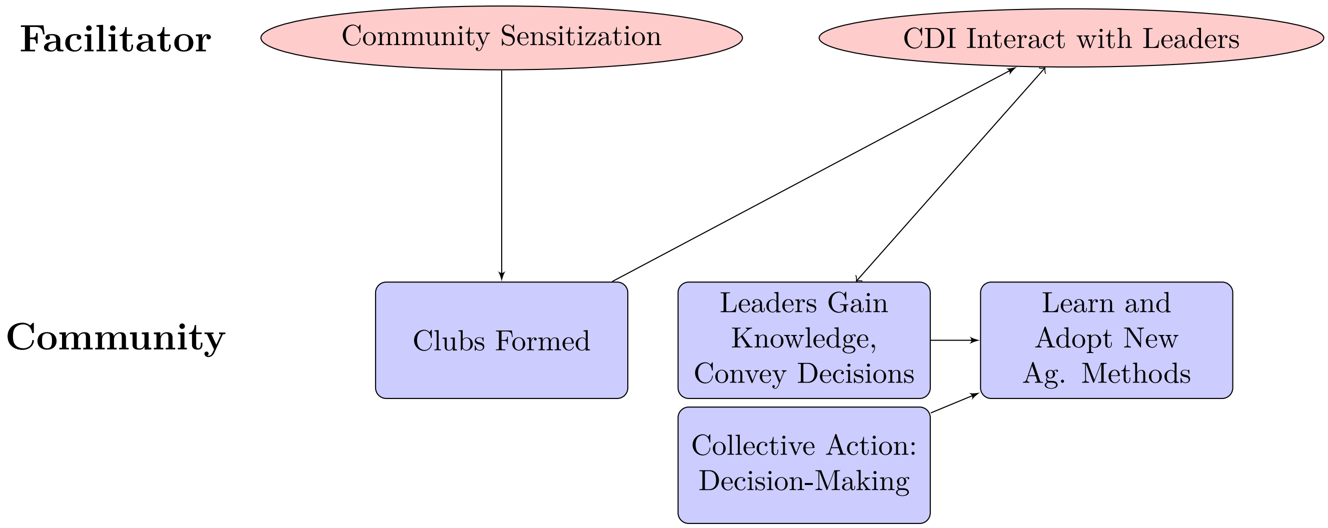


Figure 4.1: CDI's Influence on Community Farmer Clubs

club, are invited to training sessions held on the Anchor Farm to learn about a menu of novel agricultural production methods around integrated soil and fertility management (ISFM). These methods are taught on demonstration plots at a CDI-owned facility (and described in further detail in Maertens et al. [2017]). Lead farmers are encouraged to disseminate knowledge via group-managed demonstration plots in their own villages — this facilitates group-level learning-by-doing. The new production methods introduce new avenues through which the club must engage in collective action, though three stand out as particularly important: 1) sharing knowledge about new production methods, often by working alongside one-another on club-managed demonstration plots, 2) raising funds to rent a demonstration plot in the village, and 3) acquiring inputs (on credit) from CDI.[3]

In this way, the degree to which the club remains active and benefits from CDI pro-

[3]For CDI, the ultimate objective is to increase rates of technology adoption among farmers — especially those technologies that are more difficult to learn in the absence of CDI interventions. In our context, these technologies include the use of herbicides, innoculants, pesticides, organic fertilizers (composting), and crop rotation schemes. Along with revenue from sale of produce harvested on its Anchor Farm, CDI generates revenue from interest payments tied to inputs acquired by farmer clubs and revenue generated as clubs pay fees to store produce in CDI warehouses.

grams depends on the club leaders' engagement with CDI leaders and the club's capacity for collective action.[4] Thus, it is natural to ask whether the nature of CDI's engagement with the farmer clubs simultaneously depends on its preferred mode of interaction through club leaders and the club's decision-making process. For simplicity, we assume that there are roughly two types of clubs: those whose leaders make decisions in a decentralized fashion (following conversation with club members), and those whose leaders make authoritative decisions on behalf of the club. Through conversations with the field officers, we know that they prefer working with "responsive" leaders relative to unresponsive leaders. This presents a challenge for clubs whose decisions are made in a decentralized manner — the leaders of these clubs will naturally be unable to be as responsive as clubs whose leaders hold more power towards the club's decision. Thus, one of our hypotheses is that club's with centralized forms of power are more likely to interact with the CDI facilitators. In what follows, we are initially agnostic about which type of decision-making style is consistent with higher levels of collective action in our context. We explore this question descriptively in our results section and show that, along all indicators, clubs with decentralized decision-making processes demonstrate a greater capacity for collective action.

Given this fact, we also remain ambiguous about the extent to which CDI's projects lead to its desired outcomes in the two types of clubs. If CDI is engaging with clubs that are less capable of collective action, we may see more of a change in club leaders' knowledge

[4]Our focus in this article is the interaction between the club's decision-making process and its ability to benefit from CDI's services. We are aware that a club's ability to harness the cooperative potential of its members depends on many factors in addition to its decision-making process. Similarly, there are many factors that determine the degree of communication between CDI facilitators and club leaders apart from the way in which the club makes decisions. However, given that the aim of many CDD projects is to increase participation in the decision-making process and that rules of decision-making play an instrumental role in the evolution of institutions for collective action [Ostrom, 1990], we focus our discussion and analysis around the interaction between clubs' decision-making rules and eventual club outcomes. Additionally, there are empirical justifications for our focus on a club's decision-making process; specifically, in a section 4.3.7 we show that club-level fixed effects explain half of the variation in individual giving in public goods games and in section 4.4 we show that the decision-making process employed by a club accounts for roughly twenty percent of this club-level variation. Thus, the method of decision-making likely plays an outsized roll in describing a club's capacity for collective action.

and adoption outcomes than non-leaders. Conversely, if collective action drives adoption decisions, we may see more of a change in clubs with decentralized decision-making processes even if they have less interaction with CDI. We also explore these patterns in our analysis.

4.3 Data

We collected the data for this study as part of an impact evaluation. In 2014, CDI worked in three districts in central Malawi: Mchinji, Dowa and Kasungu. Districts in Malawi are further sub-divided into Extension Planning Areas, or EPAs, and the CDI program was covering all EPAs in Mchinji, but only a subset of the EPAs in Dowa and Kasungu. Together with CDI, we selected two EPAs as study sites among the remaining EPAs in which CDI had not yet worked prior to 2014. Chibvala EPA, in Dowa district, and Mtumthama EPA, in Kasungu district. The total number of villages in these two EPAs amounts to 360; we selected the 303 villages which had more than 50 households and randomly selected 250 from this set. Half of these 250 villages, again randomly selected, were invited to participate in CDI's program activities, i.e., these were the treatment villages in the impact evaluation.

As the CDI program works through farmer clubs, CDI, after having introduced their program to village leaders, asked representatives of the 125 treatment villages to establish clubs of farmers to participate. The clubs were required to have between ten and twenty members, of which 50 percent are women, and to self-select a lead farmer. In total, 87 out of 125 villages formed farmer clubs (53 villages formed more than one club, in which case one club was randomly selected as part of this study). These 87 clubs form the sample for this study.

We collected data in 2014 and in 2015. In 2014, the data include a public goods game, household surveys and village surveys. In 2015, the data include a second public goods game, focus group interviews, and interviews with club leaders. We discuss these data sources in turn below, and present relevant descriptive statistics.

4.3.1 2014 Public Goods Game

In this sub-section, we describe the public goods game. For further details, refer to Appendix C.1.1 for the game played in 2014 and C.1.2 for the one played in 2015. We first describe the data collected in 2014. We invited all club members to a central location in the village and recorded, in private, their age, gender, education level and acreage of land owned. In total, we conducted 87 games with 1,084 club members (representing about 75% of all club members, or an average of 12.5 per club). Panel A of table 4.1 describes the sample. On average, club members are 38 years old, received five years of education and own close to 5 acres of land. Roughly half (48%) of club members are female.

After collecting this information, we explained the game to all members present: Each club member was asked to divide 400 Malawian Kwacha (equivalent to one USD at the time of the game and provided by us) into two shares. One share, labelled the "individual account," would be the club member's money, i.e., the club member owns this money and decides on its use. The other share, labelled the "common account," was placed in an envelope and shared with all club members, i.e., the club members together decide on its use. The money placed in the "common account" envelope, once aggregated, was multiplied by two. We illustrated this multiplication process with actual bills. We then emphasised that the decision as to how much to place in the common account belongs to each individual and is a completely private decision.

Before the club members made their decisions, but after the game was explained, we gave the club members the opportunity to discuss how the money in the common account could be used. We did not monitor the process by which this decision was made, and did not impose any time constraints.

We then asked the club members to disperse and make their decision, individually and in private. We recorded, in a confidential manner, each member's decision. In addition, we also contributed an unknown - to the club members - amount (400 MK) to the common account, so that no-one could derive the contributions of other members from the total amount in the common account. Once each club member made their contribution decision, we collected all "common account" envelopes, added our own envelope, mixed up the envelopes, and opened them. We then counted the total amount in front of the club, added an equivalent amount and returned the full amount to the club.

Panel A of table 4.1 summarises the main result of the game: on average, club members contributed 43% of their endowment to the common account. Figure 4.2 reveals the extent of variation in individual contributions to the common account. Each participant received eight 50 MK bills, which is why we divide the histogram in figure 4.2 into eight bins. We see here that a plurality of club members (24%) contribute 100 MK followed by 200 MK (23%), 50 MK (17.9%) and 400 MK (13.4%).

4.3.2 2015 Public Goods Game

In October-November 2015 we returned to the same (and 13 additional) CDI clubs one year after the first series of public good games were played and introduced a similar version of the game with random variation in the way in which groups decided on the use of the funds in the common account.[5] The framing for the game remained roughly consistent with the game played in 2014: we asked each club to select a public good to invest in using proceeds from the game. The game was altered in one significant way that introduced random variation in the decision-making rule applied by each club during the course of the game. Half of the

[5]The 13 additional clubs come from the same villages as the original 87. In baseline, we only included one club per village in our survey - this club was the same to play the game in 2014. In 2015, we allowed additional clubs in the same 87 villages to participate in the game in order to increase our sample size to 100 clubs.

clubs were randomly selected to utilize a rule in which they were asked to reach consensus through democratic deliberation while in the remaining clubs decisions for the uses of the funds were made by club leaders before others were introduced to the game. Henceforward, we call the former treatment "deliberative democracy" and the latter "leader-driven." As figure 4.3 indicates, half of the 100 CDI clubs in our sample played one of the two versions of the game.

In both versions, we first informed the club leaders that during the game we would be presenting them with an alternative means of decision-making than the one adopted by the club itself. Specifically, we invited them to consider the experimental method of decision-making as one they could gain insights from when considering the role of different modes of decision-making in influencing group outcomes. In the leader-driven treatment, we informed the club leaders about nature of the game and then invited them to decide how the funds in the common account will be used by the club. In the deliberative democracy treatment we informed the leaders that we would be inviting each club member to share their thoughts on how the common account should be used and that members would be invited to share their thoughts in a random order. After each member shared his or her thoughts, the leaders would be asked to facilitate a conversation in which the group would reach a consensus regarding the intended use of the common account.[6] Once a decision was made in either the leader-driven or deliberative democracy version of the game, the intended use of the public good would be announced to the entire club and club members would be invited to privately contribute to the common account in the same manner as in the 2014 game.[7]

[6]We also emphasized the importance of valuing each club member's opinions equally and not forcing a club in a particular direction when consulting on the final use of the common account.

[7]Between 2014 and 2015 the value of a USD increased from close to 400 Malawian Kwacha to 500. Thus, in 2015 we distributed 500 MK and in 2014 we distributed 400 MK, both in 50 MK denominated notes, to each club member as their endowment for the public goods game.

4.3.3 Focus Groups

To gain insights into the nature of the decision-making processes utilized by the farmer clubs, we carried out focus group discussions with ten randomly selected clubs. In each instance, we invited all club members to a central location and, following Morgan [1997] and Krueger and Casey [2015], we facilitated a structured one-hour conversation around a small set of: (1) engagement questions - constructing a social network graph and documenting the history of the club, (2) exploration questions - focusing on the constraints and opportunities of club-based activities, and (3) exit questions - concluding with future plans and hopes for the club. The discussions were led by two experienced local Malawian researchers, one male and one female.

Most questions were addressed to the club. For instance, the club was asked "What are the challenges of managing a demonstration plot together as a club?" Members were encouraged to talk freely among themselves. For some questions, individual responses were required. For instance, club members were individually asked "Who (of the club) did you know before you formed the club and in what capacity?".

The most important discussions relevant to this study involved the following two questions: "How does your club generally make decisions?" and "Why was this decision-making process chosen?" From the ensuing discussions, we gleaned that clubs do not strategically choose decision-making methods but rather adopt whatever collective decision-making methods they are accustomed to using in their village. Half of the ten clubs interviewed stated that they have a democratic process in which they hold discussions to determine directions for collective action while the other half suggested that their leaders have the final say over the club's decisions. In the latter case, the leaders often stated that they discuss options with club members prior to deciding upon actions themselves. Among the more democratic clubs, clubs appeared to be more committed to reaching agreement through discussions while stating that when there are disagreements, the club's decision follows the majority rule after a vote. In effect, voting was often seen as a last resort, in case agreement could not be reached.

4.3.4 Household Survey

We administered a household survey among the households of four randomly selected club members and the club's lead farmer for each of the 87 clubs. In each case, we interviewed the head of the household. A note on sample size: While we have 435 (87 by 5) CDI households covered in the household sample, only the households with presence at the game are included in the descriptive statistics and analysis here. This leaves us with a sample of 402 matched households. The survey modules include (among others) the demographic characteristics of the household members, household assets and the household's social network and club memberships.

Social Networks

The respondent was asked to detail the nature of their relationship to each of the members of the farmer club.[8] Thus, if there are ten members in a club, then the respondent was asked to detail their relationship with each of the other nine members (excluding him/herself). We formulated and asked the following four questions (borrowed from Conley and Udry [2010b]): (1) "Do you know who this person is?" (2) "Have you asked this person for advice about your farm in the past year?" (3) "Could you approach this person if you had a question about farming?" and (4) "Would you trust this person to look after a valuable item for you?"

Individual responses to each of these questions are reported in panel B of table 4.1.

[8]For arbitrary groupings of people who participated in the randomized version of the public goods game, we documented the nature of each individual's relationship with each other game participant. Here, we also have detailed information on the nature of kinship ties and the frequency of conversation among individuals.

On average, the respondent knows 88% of other club members, seeks advice from 24%, can approach 80% of club members for farming advice, and can trust 68% of other members to hold valuable items (the latter 3 statistics are unconditional averages).

Club Decision-Making

The respondent was asked to list the civic associations that the household participates in: i.e., to list for each member of the household the organizations in which he or she participated. For each organization that the respondent (personally) belonged to, we asked a series of follow up questions about the organization (sourced from Grootaert et al. [2002]), including: "How does the group usually make decisions?"[9] Respondents could choose among the following responses: (1=) "The leader decides and informs the other group members" (2=) "The leader asks the group what they think and then decides" or (3=) "The group members hold a discussion and decide together", or (4=) "Other."

Panel C of table 4.1 shows individual responses to this question. A note on sample size: a significant sub-section of the respondents were not personally involved in a CDI club (rather another member of the family was) and, among those that were involved, some stated that their club had yet to meet (and hence felt they could not respond to our questions). We remain with 261 responses that capture information regarding the decision-making processes present in our farmer clubs.

Of the 261 responses, roughly half of the respondents indicated a more leader-driven decision-making process responsible for club decisions - 51.3% of respondents chose option number (1) or (2). 41% of respondents indicated a democratic decision-making process; this is option number (3) and only 8% of the respondents chose "other," indicating that the

[9]Other follow up questions include: "How often did the group meet in the past year?", "Overall, in your view, how effective is the group's leadership?", "How strongly do you agree with the following statement: I am able to express my views at group meetings?", and "How strongly do you agree with the following statement: I am able to influence the views of others at group meetings."

first three options sufficiently outline the set of decision-making methods employed by the majority of the clubs.

Note that within-club responses to this question may differ despite the fact that the question solicits information regarding a club-level process. Certainly, subjective perceptions of, and experiences with, the decision making process may differ depending on one's experience with the club. However, we are primarily interested in whether a club makes decisions in a *relatively* democratic or leader-driven manner. Recall that the focus group discussions help us understand that there are degrees of discussion-based decision-making adopted by the democratic clubs as well as various forms of member contributions in leader-driven clubs. In this way, the responses can be thought of as providing information on the placement of a club along a spectrum of decision-making methods between two extremes: fully democratic and fully leader-driven. The average club-level response to this question will allow us to identify where a club lies along this spectrum.[10]

Table 4.2 provides summary statistics at the club-level for relevant variables in our analysis. In total, we lose information regarding decision-making processes for 13 clubs that played the public goods game because either we did not capture information from a household member with personal involvement in the club, the club had yet to meet, or due to a combination of these. Thus, we restrict descriptives of club-level data to the 74 remaining clubs with an average of 3.5 responses per club. Panel A in table 4.2 reports the club-level averages. The within-club average of the decision-making variable is 2.29 and the median of the within-club average is 2.2 (Recall that this number is between 1 and 3 where 1 is the most leader-driven process while 3 is the most democratic process). To further ease interpretation of results, we also create a binary measure. We divide clubs into two mutually exclusive groups based on whether they are above or below this median value of 2.2 (See appendix C.1.2).

[10]In calculating the average, we omit responses that answered "other."

4.3.5 Village Questionnaire

We administered a village questionnaire in each of the 87 villages among a knowledgeable individual, often the village head or secretary to the village head. This village questionnaire covered information on the village's (and hence the club's) distance from paved roads, population, access to NGO or governmental extension workers, price of daily labour during harvest, and involvement with other civic organizations. Panel B of table 4.2 presents relevant village-level descriptive statistics for the 74 villages used in our analysis. Note the large variation across villages in these measures. Villages report being an average of 1.8 kilometres (km) away from paved roads; however, the furthest village is 13 km away and half of the villages are less than 0.3 km away. The average village size is 69 households, however the largest village has over 400 households. Roughly 30% of villages have never been visited by an NGO extension worker - which suggests that even though clubs are formed by CDI, many farmers have only interacted with CDI through the organizational structure CDI espouses. A day's worth of labour (from a single labourer) during harvest also varies significantly across villages with an average of 1,101 MK and a standard deviation of 1,170 MK.

4.3.6 Leader Survey

Finally, in 2015, one year after most clubs had been operating as CDI farmer clubs, we surveyed the leaders of the clubs to learn more about club activities. These surveys were conducted prior to playing the 2015 round of the public goods game. The club's chairperson, lead farmer, secretary and treasurer were asked to congregate in a central location to provide collective responses to a series of questions about the club's interaction with CDI field officers, the decision-making process, frequency of meetings, use of funds, and description of primary activities. A full set of questions posed to leaders is available in Appendix C.1.2.

4.3.7 Motivating club-level Analysis

Before embarking on the analysis of these data, we highlight the importance of the club's operating context in predicting contributions to the common account. The observation that individuals contribute 43% of their endowment to the common account is similar to patterns of contributions in other studies utilising variants of a public goods game. For example, a review by Chaudhuri [2011] notes that individuals on average contribute between 40% and 60% of the experiment's endowment. Nevertheless, these contributions exhibit considerable, even multi-modal, variation similar to the distribution we discussed above. However, appendix figure C1, which shows the club-average distribution, shows a more balanced distribution of club-level contributions, which suggests key differences in club vs. individual contribution behaviour. This is also reflected in panel C of table 4.2 which shows that the per-club average share of contributions closely correspond to average individual contributions (42%) but with a smaller standard deviation (21% vs. 30%).

We first explore individual correlates of common account contributions by regressing individual contributions against individual characteristics in table 4.3. We find no statistically significant correlation for gender and age while educated and wealthier individuals contribute significantly more on average. In column (2) we incorporate club-level fixed effects and show that these do not change the direction of coefficients relative to column (1). However, they are able to explain roughly 50% of the variation in contributions as exhibited by the jump in the adjusted R^2 value from 0.04 to 0.52. Indeed, a one-way ANOVA regression provides an intraclass correlation coefficient of 0.51, suggesting that half of the variation in contributions is strongly related to club-level factors.

This difference is likely due to the local economic, social, and political context each club is embedded within, a context that we have attempted to measure through the data discussed above. To elaborate, while the agency to contribute to the public good belongs to the individual, individual factors alone will not help to understand the determinants of cooperation in the farmer club. Recall, in our public goods game, the club gets to keep and spend the multiplied common account funds towards their own ends. We have already described the construction of the primary club-level variable describing a club's political, or decision-making, context.

Other economic and social factors that influence cooperation include aggregate levels of wealth (land size and asset holdings), education, age and share of female members. To construct these aggregates, we generate within-club measures of averages and standard deviation to capture both levels and distributions of relevant club-level variables. We construct similar measures of within-club social interactions. Given the nature of the random-within-club sample design, aggregate measures constructed using survey data are assumed to be representative of the club. Finally, local context can be partially characterised by the village-level variables which capture village size, market access and familiarity with civic associations.

4.4 Club-Level Decision-Making, Village Norms and Collective Action

Prior to analyzing the relational dynamics between CDI and the farmer clubs it organizes, we focus first on the decision-making processes operating within CDI clubs. We seek to understand how this feature of farmer clubs influences their capacity for collective action. We focus first on analyzing the influence of decision-making rules on cooperation in the 2014 public goods game and find that democratic clubs are significantly more cooperative than authoritarian clubs. As suggested by the focus group discussions, we show that decision-making rules in CDI farmer clubs are highly correlated with the rules adopted by "other" associations within the village, suggesting that decision-making norms evolve at the village-level and are difficult to influence. We present evidence for this assertion by showing that there is no explanatory power associated with random changes in decision-making rules imposed on clubs in the 2015 public goods game. Finally, we present evidence suggesting that the patterns of decision-making are qualitatively different from one another due to differences in cooperation resulting from interactions between club characteristics, namely social connectivity and club size, and the club's decision-making process.

Table 4.4 presents mean values of 2014 club characteristics by a dichotomous characterization of the decision-making method utilized by CDI clubs. The last column reports P-statistics associated with t-tests in which the null hypothesis is that the sample mean is equivalent in the two decision-making clubs. Out of 26 variables tested, only 3 means differed significantly from each other (at the 90% confidence level). First, clubs using democratic decision-making methods tend to have two fewer members participate in the public goods game than those using centralised regimes. Second, the mean age of club members in clubs using democratic methods is two years higher than the centralised regime. Third, 20% more of the villages in which clubs employed democratic decision-making methods were not visited by government extension workers in the 12 months prior to the survey. It is noteworthy that the decision-making process is not systematically related to any of the network variables, which may proxy for pre-existing norms of cooperation (see panel B in table 4.4). This suggests that village decision-making norms are sticky and that club-level decision-making processes are selected on the basis of "known" rules for decision-making at the village level. While we are not arguing for a causal relationship between the decision-making method employed by the club on cooperative outcomes, it is striking that there are very few meaningful statistically significant differences between the observable characteristics of the two types of clubs.

Empirical Specification

To understand the relationship between cooperation and club characteristics, we present a basic empirical specification. Formally, we first denote the farmer club S_j as the unit of analysis and then regress the average contributions to the common account against the decision-making process employed by the club alongside other covariates as follows:

$$C_j = \alpha + \beta_1 R_j + \beta_2 S_j + \beta_3 X_j + \beta_4 V_j + \epsilon_j \tag{4.1}$$

where each club is represented by subscript j. The dependent variable, C_j, represents the average share of the endowment contributed by club members. Variable R_j represents club j's decision-making method which can be either leader driven (0) or democratic (1) - thus, β_1 can be interpreted as the effect of democratic decision-making on contributions in the public goods game in percent terms. S_j represents the degree of social connectivity within the farmer club — we are primarily interested in whether club members can "approach" one another for farming advice since this quality of social relationships is the underlying reason the farmer club model is utilized by CDI.

Vector X_j includes club-level variables such as the club mean and standard deviation of age, gender, years of education, land, and asset stock for all club members and the total number of game players. In other words, we aggregate the variables in panel A of table 4.1 and include them in the estimation of equation (4.1) by taking both the per-club mean and standard deviations of these measures. [11] V_j contains village-level characteristics that may influence the value of the club's public good: the village's distance to a paved/all-weather road, the number of households in the village, the presence of NGO or governmental extension workers, the value of labour during harvest, and the number of civic associations present in the village.[12]

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[11] Among these variables, information regarding asset stocks is taken from the household survey which randomly selects five households whose members belong to a CDI club - thus, aggregate levels of asset stocks are assumed to be representative of the club's membership.

[12] A number of the variables in the analysis are skewed quite far to the right. Due to the small sample

A second approach involves using the focus group discussions insight that farmer clubs adopted decision-making methods correspond to decision-making methods they have experienced in other club settings within the village. Thus, instrumenting for club-level decision making methods using methods used in other village settings allows us to understand whether unexplained variation in cooperation is due to village-level, rather than the club-level, forces. Recall, our household survey sample includes five randomly selected households who are not members of CDI clubs; however, we still collect information on the nature of their engagement with civic organizations at the village level and their respective decision-making processes. We use this information to construct a village-level measure of decision-making employed by all non-CDI village associations.[13] In other words, we construct a village-level average of the decision-making methods employed by all non-CDI clubs in which survey respondents participate.

Naturally, this variable is only available in CDI villages in which survey participants report involvement in civic associations other than CDI. Panel D of table 4.4 shows that, of the 47 villages for which we can construct a measure for the instrument, 24 are in villages for which the CDI club uses democratic decision-making methods. A simple t-test suggests that the instrument holds some promise as the decision-making norms are significantly more democratic in non-CDI clubs in these villages ($p = 0.07$). To strengthen the precision of our instrument, we omit four cases in our data in which the absolute difference between the continuous measure of decision-making in CDI and non-CDI clubs is larger than one; it is unlikely that the CDI decision-making method was chosen out of extant decision-making

in the analysis, we apply log transformations of the following variables to ensure our results are not biased by outlier observations: mean and standard deviations of land and asset stock, distance from paved road, the number of households residing in the village and the value of labour during harvest. Table C4 in the appendix provides detailed summary statistics of all of the variables as they are used in the analysis.

[13]In some cases, CDI households also participate in other clubs at the village level. To supplement and add precision to our measure of village-level norms, we include information from these cases in the construction of our instrumental variable.

norms in these villages.[14] After omitting these 4 observations, the same t-test shows a stronger relationship between decision-making in CDI clubs and other village associations (p = 0.004). We don't argue that this variable is necessarily excludable from a second stage in which we regress democratic decision-making against the average share contributed by the club in the public goods game. Nevertheless, the IV exercise is valuable in that it sheds light on whether village- or club-level forces drive cooperative outcomes — if the OLS correlation is upheld in the IV regression, then village-level norms around decision-making processes are likely to influence our outcomes. This would provide further evidence of the "stickiness" of institutional norms in the villages in our study.

2014 Game Results

Table 4.5 presents results from estimations of equation 4.1. Each column progressively adds additional controls to assess whether omitted variable bias is a threat to our analysis. Column (1) includes the effect of democratic clubs (relative to leader driven clubs) and shows that democratic clubs contribute 14 percentage points more towards the common account (44% more than leader driven clubs) on average. Column 2 adds club-level controls, column 3 adds village level controls, and column 4 adds our measure of social interactions. Results presented in table 4.5 demonstrate that the controls have little effect on the coefficient of interest - indeed, adding additional controls marginally increases the coefficient associated with democratic decision-making, evidence that omitted variable bias may not be a significant problem for our analysis and is more likely to attenuate the effect of democratic decision-making than bias it upward. Furthermore, it is quite striking that the difference in the Adjusted R^2 is 0.18 between columns (4) and (5). Thus, once accounting for confounding factors, the dichotomous decision-making variable accounts for nearly *20% of the variation*

[14] Our results are robust to the use of an instrument inclusive of these 4 observations; however the instrument is weakened in this case.

in the average contribution to the common pot in our dataset.

We find that the total share of contribution decreases by 1 percentage point for each additional individual in the club participating in the public goods game; this finding is consistent with both theory and empirical results which have found that free-riding increases as the number of participants grows. We also find that among the club-level variables, only average land size significantly influences public goods contributions. The negative correlation suggests that clubs with more farming resources (land) may value club-provided public goods less than others. However, clubs with greater variation in the distribution of land and education (measured using within-club standard deviations) see higher contributions, on average, than other clubs. Finally, the effect of our measure of social interactions is not significantly different from zero.

The analysis presented in table 4.5 uses a binary measure of the club's decision-making process. We can also treat club decision-making as located along a spectrum where fully leader driven and fully democratic processes occupy the two extremes. The use of a continuous measure of decision-making can provide information on the position of each club along this spectrum. Appendix table C5 provides estimation results of equation 4.1 using this continuous measure of club decision-making. The results are consistent with findings from estimations using the dichotomous measure but point estimates increase, suggesting that clubs towards the democratic end of the spectrum engage in more cooperative behaviour. [15]

Finally, table 4.6 presents results of the IV estimation in which we use the continuous

[15] Columns (1) and (2) of Table C5 are analogous to columns (3) and (4) of table 4.5. The difference between the ends of this spectrum are highlighted by increasingly larger coefficients in columns (3), (4), and (5) in which clubs are only included in the analysis if, respectively, more than 1, 2, or 3 individuals responded to survey questions providing information on the method of decision-making employed by the clubs. In this sense, columns (3), (4), and (5) represent progressively more accurate estimates of the specific location of the club along the decision-making spectrum. Although unreported, this is verified by the coefficient on the within-club mean standard error of the decision-making variable - it has progressively less significance in predicting cooperative behaviour across columns of this table. This follows from logical argumentation using the law of large numbers - the sample average moves closer to the true mean as the number of observations increases. Thus, clubs with more responses more accurately describe the true decision-making process.

measure of decision-making methods as the endogenous (CDI clubs) and exogenous (non-CDI civic associations) regressor.[16] In order to compare the results of the two-staged least squares IV estimation with the OLS estimation associated with the IV sub-sample, we present the limited-sample OLS results of equation 4.1 in column (1) in table 4.6. The instrumented coefficient is positive and statistically significant and the first stage is strong with an F statistic of 16.5. Moreover, we cannot reject the exogeneity of the instrument according to a Wu-Hausman test ($p = 0.30$). This result suggests that village-level decision-making norms are strong enough to influence cooperation *within clubs*. We expect that the coefficients are slightly inflated relative to their comparison OLS specifications because the instrument highlights the extent of cooperation in which democratic decision-making norms are more present across the population, making them easier to apply and benefit from in club settings.

Qualitative Differences in Clubs with Differnt Rules

Deliberative democracy theorists suggest that there are situations in which inefficiencies can emerge when using a deliberative democratic approach that may not present in a leader driven approach. To show the qualitative differences in how the decision-making processes in our sample influence cooperation, we test for the presence of these inefficiencies to confirm mechanisms associated with deliberation in club settings. First, we expect that as the number of individuals increases within a democratic club, agreement is more difficult to reach via deliberation. Figure 4.4 displays a flexible polynomial relationship between average contributions and club size by the decision-making style employed. The left panel, which presents average contributions in leader driven clubs and the number of game players, shows what may be a slight negative relationship between the number of participants in the public goods game and the amount of cooperation. This is expected if larger numbers of participants

[16] Table C7 in the appendix presents results of the IV estimation in which the dichotomous decision-making variable is the endogenous regressor (CDI) and the continuous variable is the exogenous (non-CDI) regressor.

increase free riding behaviour.

A different dynamic emerges in the right panel of figure 4.4, which includes only democratic clubs. The right panel presents a strong inverse-U shaped pattern between the number of participants in the game and average contributions. When club sizes are small, additional members increase average contributions, perhaps because of the contribution of new insights in club discussion. However, beyond a threshold of around 11 or 12 individuals, additional members decrease average contributions, perhaps because it becomes difficult for the club to identify a public good compatible with (club) preferences.

Similarly, deliberation may lead to less desireable outcomes if the participants in deliberation are uncomfortable speaking and listening to one another. Table 4.7 interacts democratic clubs with our de-meaned measures of social interactions. Column (1) examines the heterogeneous effect of our preferred measure of social interactions, aggregate "approachability" of club members, while column (2) attempts to isolate the effect of approachability by controlling for our other measures of social interactions. In this way, we are extracting the direct effect of social interactions out of the approach measure to get the cleanest measure of whether the club possesses the capacity to engage in open discussion among club members.

We find (column (1)) a negative effect associated with increased approachability of club members in leader driven environments and a null effect in democratic clubs - in other words we cannot reject a Wald joint hypothesis test that the sum of the coefficients in front of the interacted terms is different from zero. In leader driven clubs, a ten percent increase above the mean decreases cooperation by 8 percentage points. The negative coefficient suggests that, among the direct effects of social interactions in the public goods game, the negative effects of social interactions dominate the positive effects in clubs whose decisions are made by leaders. However, much of this negative effect appears to dissipate in democratic settings. To check for the robustness of this result, we control for the direct effect of other measures of social interactions in column (2) and see that the coefficient on the interaction term associated with approachability is significantly positive while the direct effect is not significantly different from zero.

Finally, in our leader questionnaire we ask the leaders a series of questions about how they enforce defectors of club activities that require collective action.[17] One of the predominant farmer club activities involves providing loans to club members. Naturally, this creates the possibility that club members will default on repayment. We ask club leaders to indicate the likelihood that a defaulter will be punished by the club either by fining the individual, kicking them out of the group, or some other form of punishment. Figure 4.5 shows that leaders of authoritarian clubs believe such a punishment is likely — 95% of such leaders indicate that punishment is either highly likely or somewhat likely. Only 75% of the leaders of consultative clubs indicate that punishment is likely. Consultative clubs are also least likely to have a set of rules that determine outcomes for defectors: 61% of authoritarian clubs rely on a predetermined set of rules to adjudicate outcomes in such settings while only 18% use predetermined rules in consultative groups. 70% of consultative groups discuss each individual case of defection separately before coming to a decision.

Experimental Attempts at Inducing Changes in Decision-Making Fail

We claim that the trenchant nature of decision-making norms in our setting makes them difficult to manipulate. One way to confirm this claim is to obtain null results in the 2015 version of the public goods game in which decision-making rules are randomized.

Columns (1) and (2) in table 4.8 show the effect of deliberative decision-making on contributions to the public good game in established CDI farmer clubs. We cannot reject a null treatment effect when the treatment is defined as the random selection into a deliberative

[17]The leader questionnaire also asks the same question about decision-making in clubs that was posed in the 2014 household survey. Since all leaders respond to this question simultaneously, we treat responses as a categorical variable of the decision-making method in the club with three categories: authoritarian (leader decides), mix (leader consults, then decides), and consultative (group decides via discussion).

decision-making rule in established CDI clubs. This confirms our original assumption that the randomization of decision-making rules in established community organizations would not be effective, and that such a study would need to rely on observational data. Established decision-making rules in such clubs are likely too sticky to be manipulated by outsiders - clubs may make decisions in public goods games as though their own decision-making rules will prevail after funds are transferred to the clubs.

Natural Forms of Collective-Action in Clubs

Finally, one might wonder whether contributions in the public good game lead to increased capacity for collective action in reality. In the 2015 interviews with club leaders we gleaned information on aspects of club functioning at least one year following the initial sensitization meetings held by CDI. We asked leaders 1) the number of meetings they held in each season, 2) whether the club engages in providing loans to its members, 3) the three most important club activities, and 4) itemized lists of club expenditures over the last year. In category 3), we isolated instances in which the clubs indicated that "helping each other" was one of the most important club activities and in category 4) we divide total expenditures into farm/field-rental related expenditures and farming input expenditures — two of the more important types of farmer club expenditures given the nature of their activities.[18] This results in six measures that provide reasonable proxies for a club's capacity for collective action. Figure 4.6 shows a very consistent trend in which we compare the averages of all measures across decision-making categories and additionally provide the 90% confidence intervals for each measure. Each variable is larger among clubs with decentralized decision-making methods relative to centralized, authoritarian, decision-making methods. Variables associated with club expenditures on agricultural inputs are statistically significantly higher in the former

[18] We included instances in which leaders cited "ganyu" as one of the most important activities in our "helping each other" measure. Ganyu is a form of labor-pooling during labor-intensive farming seasons in Malawi.

type of club. Thus, we assert that clubs with decentralized power structures are, on average, more cooperative than clubs with more vertical power structures.

4.5 Club-NGO Interactions

We have shown that consultative farmers clubs are capable of higher degrees of collective action than authoritarian clubs. What remains to be seen is whether this leads to greater levels of interaction with CDI, and hence effectiveness of its community driven development program. As mentioned in section 4.2, CDI liaises with clubs via each club's lead farmer. It is reasonable to think, and indeed conversations with CDI facilitators suggest, that facilitators will preferentially interact with leaders who are more able and enthusiastic about carrying out CDI's requests. While we do not know which type of leaders possesses these qualities, we do know that authoritarian leaders can make more decisions on behalf of their clubs than leaders of consultative clubs. This suggests that CDI will be more likely to interact with the former type of leaders.

In the 2015 interview with leaders, we collected information detailing the extent of club leaders' interactions with CDI. We are able to summarize the nature of these interactions in four measures: 1) the number of CDI trainings leaders attended, 2) whether the leaders know the CDI officer by name, 3) whether they have ever communicated with a CDI agent and 4) the number of interactions the leaders have with CDI facilitators on CDI demonstration plots. Figure 4.7 summarizes these measures by decision-making method utilized by each farmer club. The patterns show that authoritarian clubs interact with CDI, on average, more than leaders of consultative clubs. Furthermore, authoritarian leaders attend a statistically significant higher number of trainings on average and interact more with CDI facilitators on demonstration plots. Leaders in "mixed" decision making clubs whose leaders consult club members before making decisions sometimes interact more with CDI facilitators than authoritarian leaders and sometimes interact less, though these differences are never statistically significant. Combining evidence from this and the previous section, it is reasonable to conclude that CDI interacts more with clubs who have lower capacity for collective action.

Finally, we demonstrate that CDI objectives — to increase knowledge and adoption rates of new agricultural technologies in farmer clubs — are less likely to be achieved in clubs with authoritarian leaders despite the increased rates of interaction with such leaders. In 2015, we conducted mid-line surveys with a subset of CDI club members to determine the degree to which CDI programs were influencing outcomes one year after initiating their program. As part of these surveys, we quizzed farmers on methods taught by CDI at trainings and demonstration plots. Additionally, we asked farmers to indicate whether they plan to adopt one of the suggested agricultural technologies promoted by CDI.[19]

Table 4.9 analyzes the extent to which knowledge scores and planned adoption rates differ across the two types of clubs. Columns 1 and 2 analyze the knowledge scores of club leaders and column 3 analyzes their planned adoption rates. We do not see much movement in knowledge scores of non-leaders so we restrict non-leader analysis to planned adoption rates in column 4. Column 1 shows that any leaders who attend any CDI training increase their knowledge of CDI introduced technologies by one point (50% increase from baseline). However, clubs with consultative decision-making score one additional point higher in the knowledge quiz. In column 2 we explore whether consultative club leaders only benefit conditional on having had interactions with the CDI facilitator. We find that the direct correlation of being a leader of a consultative club is still large, though such a leader who has also spoken to CDI leaders scores higher on the knowledge score than leaders in other types of clubs (authoritarian). This is surprising since CDI facilitators interact with fewer

[19] We ask similar questions in the control villages that are part of the broader impact evaluation. In total, we ask 20 knowledge questions and 13 questions related to the menu of technologies introduced by CDI. In order to increase the precision of the novel knowledge learned and technologies introduced, we remove the 10 most correctly answered questions and the 7 most likely to be adopted technologies in the control villages when generating sums of our knowledge and planned adoption measures.

leaders of consultative clubs than leaders of authoritarian clubs.

Column 3 switches focus to adoption plans. What is striking in this column is that leaders who participate in CDI trainings and leaders who have ever spoken with CDI facilitator are not more likely to plan adoption of new technologies. However, again, leaders of consultative clubs are significantly more likely to adopt novel CDI technologies. Indeed, they plan to adopt 300% more of the novel technologies than authoritarian clubs. This suggests that it is possible that accountability to club members drives the leaders behaviors in consultative clubs in a way that does not drive behaviors in authoritarian clubs. To examine this, we explore non-leader adoption plans in column 4 and introduce leader adoption plans as an explanatory variable. Somewhat strikingly, leader adoption plans have no statistically significant effect on nonleader adoption plans in authoritarian clubs; however, they are positively correlated with nonleader adoption plans in consultative clubs.

4.6 Conclusion

In this paper we have established that clubs making decisions via consultative, decentralized or democratic decision-making, processes are, on average, more capable of collective action than clubs with authoritarian leaders. We show this using a robust set of measures relating to this capacity that include real-world measures of club effectiveness in addition to outcomes stemming from playing public goods games in club settings. We also show that clubs select their decision-making rules out of the milleu of decision-making norms present in their village and that manipulating the club's decision-making rules does not lead to change in contributions during the public goods game. Despite the fact that CDI potentially has more to gain by engaging consultative clubs, the model of CDI's engagement with farmer clubs leads them to interact more with clubs with more responsive, likely authoritarian, leaders. We conclude by showing that, despite the fact that decentralized club leaders interact less with CDI, they still benefit from their few interactions with CDI and are likely able to diffuse the benefits of these interactions to members of their own clubs to a greater degree than authoritarian leaders. Thus, the model of interaction CDI has adopted to engage with farmer clubs, a model that is very prevalent in community driven development programs, is likely generative of systematic inefficiencies and possible elite capture.

These findings contribute to our understanding of the functioning of small, village-based, community groups in developing countries. Development programs often rely on these types of community groups to organize and implement project activities; a popular strategy given limited resources and the often-assumed ability of community members to coordinate and improve outcomes using information often inaccessible to policy-makers and practitioners. Farmer clubs, in particular, are central to contemporary agricultural development and extension programs. Often, these farmer clubs tend to be treated as a black box - one of a number of bundled project interventions. Yet, because these clubs are characterised by politics, agendas, and complex social relationships, a development program built around such clubs as the primary channel for dissemination of information, learning, or stakeholder collaboration may succeed or fail based on the club's socio-political structure. Given the individual costs of coordination and participation, such clubs are beneficial only to the extent that they are capable of coordinating to produce an outcome that dominates what participant farmers could achieve individually.

More than anything, this study introduces a new set of questions that need to be addressed by researchers and policy-makers. Two questions stand out when thinking about the interaction of governments/NGOs that run CDD programs and the communities they interact with. How can CDD programs interact with heterogeneity in local communities in a practical and effective manner? What models of interaction between CDD programs and local communities lead to preferential interaction with communities that are naturally inclined to have higher levels of participation in decision-making?

Then, a striking feature of our results is that we see much higher capacities for collective action among consultative decision-makers. Why do such decision-making methods lead to higher levels of cooperation? How do village institutions evolve into such modes of decision-making in the first place? These questions are particularly important to address if the means by which regional institutions interact with local institutions are generative of more authoritarian decision-making methods, which is a reasonable outcome due to the probable regional-to-local communication efficiency gains stemming from communicating with leaders who hold more power over collective decision-making.

Tables and Figures

Table 4.1: Individual Descriptive Statistics

	N	Mean	Sd	Median	Max
Panel A - Demographic Variables:					
Share Contributed in Game (0-1)	1,079	0.43	0.30	0.4	1.0
Female	1,059	0.48	0.50	0.0	1.0
Age	1,082	38.77	13.12	36.0	82.0
Years of Education	1,073	5.39	3.49	5.0	12.0
Land Size (Acres)	1,080	4.86	10.47	3.0	260.0
Panel B - Social Ties - % of Club Members:					
Known	398	0.88	0.15	0.9	1.0
Sought Advice From	398	0.24	0.29	0.1	1.0
Could Approach for Advice	398	0.80	0.24	0.9	1.0
Could Trust with Valuables	398	0.68	0.32	0.8	1.0
Panel C - Club's Decision-Making Process:					
The leader decides and informs the group	261	0.17	0.38	0.0	1.0
The leader decides after consulting the group	261	0.34	0.47	0.0	1.0
The group decides through consultation	261	0.41	0.49	0.0	1.0
Other (unexplained)	261	0.08	0.27	0.0	1.0

The discrepancy in the number of observations results from the following: contributions to the common account and demographic variables (with the exception of asset value) are sourced from data collected during the public goods game. All other data are sourced from the household survey. Answers for data in Panel C are limited to a further subset with knowledge of their club's decision-making process.

Table 4.2: Club Level Descriptive Statistics

	N	Mean	Sd	Median	Max
Panel A - Decision-Making Method					
Continuous Measure of Decision-Making Process*	74	2.29	0.56	2.2	3.0
Heterogeneity in Responses (Mean SE)	74	0.24	0.28	0.2	1.0
Panel B - Village Characteristics:					
Distance to Paved Road (km)	74	1.83	2.75	0.3	13.0
Number of Households in Village	74	68.77	58.94	52.5	412.0
Number of Organisations from Village Questionnaire	74	1.97	1.26	2.0	5.0
No Visits by Gov. Extension (year)	74	0.27	0.45	0.0	1.0
No Visits by NGO Extension (year)	74	0.28	0.45	0.0	1.0
Price of Labour During Harvest (100 MK/Day)	74	11.01	11.68	7.3	70.0
Panel C - Other Club Variables:					
N game players	74	12.88	4.89	12.5	20.0
Share Contributed in Game (Club Average)	74	0.42	0.21	0.4	1.0

* Equal to 1 if all members chose leader and 3 if all members chose discussion. Construction of this variable is summarized in appendix C.1.2.

Table 4.3: Correlates of Individual Common Account Contributions in the Public Goods Game

	(1)	(2)
Game Data:		
Female	-0.001	-0.018
	(0.019)	(0.014)
Age	0.000	-0.000
	(0.001)	(0.001)
Years of Education	0.011^{***}	0.005^{**}
	(0.003)	(0.002)
Log: Land Size (Acres)	0.071^{***}	0.016
	(0.016)	(0.012)
Club FE	No	Yes
Adjusted R^2	0.04	0.51
Observations	1045	1045

Robust standard errors in parentheses. Dependent variable equals the percent of the game endowment (0-1) contributed by each individual.

${}^{*}p < 0.10$, ${}^{**}p < 0.05$, ${}^{***}p < 0.01$

Table 4.4: Comparing Democratic and Leader Driven Club Characteristics

	Leader		Democratic		
	N	Mean	N	Mean	P
Panel A - Club Variables:					
N Club Members	37	17.70	37	17.08	0.428
N game players	37	13.95	37	11.81	0.060*
Club Mean: Female (0-1)	37	0.47	37	0.50	0.528
Club Sd: Female (0-1)	37	0.49	37	0.48	0.540
Club Mean: Age	37	37.61	37	39.84	0.056*
Club Mean: Years of Education	37	5.24	37	5.58	0.371
Club Mean: Land (acres owned)	37	4.07	37	4.75	0.183
Club Mean: Asset Value (1000s MK)	34	127.23	37	222.09	0.160
Club Sd: Age	37	12.52	37	12.24	0.679
Club Sd: Years of Education	37	3.13	37	3.15	0.903
Club Sd: Land (acres owned)	37	3.00	37	3.62	0.479
Club Sd: Asset Value (1000s MK)	34	160.68	37	316.49	0.218
Panel B - Network Variables:					
Club Mean: Percent Known (0-1)	34	0.90	37	0.88	0.227
Club Mean: Percent Approachable (0-1)	34	0.81	37	0.82	0.598
Club Mean: Percent Sought Advice (0-1)	34	0.23	37	0.25	0.595
Club Mean: Percent Trusted (0-1)	34	0.67	37	0.73	0.200
Club Sd: Percent Known (0-1)	34	0.08	37	0.11	0.142
Club Sd: Percent Approachable (0-1)	34	0.19	37	0.14	0.119
Club Sd: Percent Sought Advice (0-1)	34	0.21	37	0.26	0.116
Club Sd: Percent Trusted (0-1)	34	0.27	37	0.23	0.179
Panel C - Village Characteristics:					
Distance to Paved Road (km)	37	1.84	37	1.82	0.973
N of HH in Village	37	65.03	37	72.52	0.588
N organisations from village questionnaire	37	1.89	37	2.05	0.583
No Visits by Gov. Extension (year)	37	0.16	37	0.38	0.037**
No Visits by NGO Extension (year)	37	0.27	37	0.30	0.800
Price of Labour During Harvest (100 MK/Day)	37	10.53	37	11.49	0.727
Panel D - Non-CDI Decision Making Norm:					
Non-CDI Organisations: Decision-Making (Continuous)$^{+}$	23	2.31	24	2.58	0.069*

Note: All t-tests are binary means tests with unequal variance.

$^{+}$ Equal to 1 if all survey respondents chose leader and 3 if all chose discussion.

Table 4.5: Effect of Decision Making Method on Cooperation in Public Goods Game

	(1)	(2)	(3)	(4)	(5)
Main effects:					
Democratic (Dichotomous)	0.14***	0.16***	0.17***	0.19***	
	(0.05)	(0.05)	(0.05)	(0.05)	
Club Mean: Percent Approachable (0-1)				-0.35	-0.34
				(0.29)	(0.32)
Club Variables:					
N game players		-0.01**	-0.01**	-0.01**	-0.01*
		(0.00)	(0.00)	(0.00)	(0.01)
Club Mean: Female (0-1)		0.09	0.11	0.10	0.13
		(0.15)	(0.15)	(0.15)	(0.16)
Club Mean: Years of Education		0.02	0.01	0.00	-0.00
		(0.02)	(0.02)	(0.02)	(0.02)
Log: Avg. Land Owned		-0.17	-0.26**	-0.34**	-0.16
		(0.12)	(0.13)	(0.13)	(0.14)
Club Sd: Female (0-1)		0.36	0.39	0.36	0.28
		(0.36)	(0.37)	(0.37)	(0.40)
Club Sd: Years of Education		0.05	0.07**	0.08**	0.05
		(0.03)	(0.03)	(0.03)	(0.03)
Log: Sd. Land Owned		0.14*	0.16**	0.21**	0.10
		(0.07)	(0.07)	(0.08)	(0.08)
Village Variables:					
Log: Distance to paved road (km)			0.07**	0.07**	0.07*
			(0.03)	(0.03)	(0.03)
N organisations from village questionnaire			0.06**	0.06**	0.06**
			(0.02)	(0.02)	(0.03)
Constant	0.32***	-0.01	-0.51	-0.37	-0.67
	(0.04)	(0.43)	(0.49)	(0.52)	(0.57)
Adjusted R^2	0.10	0.19	0.29	0.30	0.12
Observations	74	71	71	71	71

Standard errors in parentheses. Dependent variable equals the average share of the game endowment contributed by club (0-1). Additional controls were included but not reported in the following manner: columns 1-4: within-club heterogeneity in reporting decision-making methods (SE Mean); columns 3-5: village population (log), whether the village received visits from extension agents (NGO and Gov), price of daily labour during harvest (log), distance from major trading areas (log km); columns 4-5: within-club heterogeneity in social connectivity (SD).

Table 4.6: 2SLS IV Regressions

	(1)	(2)
Instrumented:		
Democratic (Continuous)	0.35*	0.58***
	(0.20)	(0.22)
Network Variables	Yes	Yes
Club Variables	Yes	Yes
Village Variables	Yes	Yes
R^2	0.52	0.48
Observations	43	43
H_0: Instrument is Exogenous		0.30
First Stage F-Statistic		16.5

Standard errors in parentheses. Column (2) shows results of a 2sls instrumental variable regression (Column (1) is estimated using OLS and only includes the sample used in column (2)) in which club decision-making is instrumented by the decision-making norm in the rest of the village. The dependent variable equals the average share of the game endowment contributed by club. Null hypothesis test results report Wu-Hausman P-values. Club-and-village-level controls are the same as in column (4) of table 4.5. First stage of estimation reported in table C6.

Table 4.7: Heterogeneous Effects of Social Networks

	(1)	(2)
Decision-Making:		
Democratic (Dichotomous)	0.19^{***}	0.20^{***}
	(0.05)	(0.06)
Approach:		
Club Mean: Percent Approachable (0-1)	-0.77^{**}	-0.19
	(0.37)	(0.56)
Democratic (Dichotomous)	0.56^{*}	0.99^{**}
× Club Mean: Percent Approachable (0-1)	(0.32)	(0.40)
Social Interaction Variables	No	Yes
Club Variables	Yes	Yes
Village Variables	Yes	Yes
Adjusted R^2	0.33	0.31
Observations	71	71

Standard errors in parentheses. Dependent variable equals the average share (0-1) of the game endowment contributed by club. Club-and-village-level controls are same as in column (4) of table 4.5. Column 2 includes controls for all other social interaction variables (club mean and club sd) associated with trust, advice, and known. Interacted social interaction variables are de-meaned.

Table 4.8: Random Variation in decision-making Rule

	(1)	(2)
Treatment:		
Deliberative Dem.	-0.017	-0.025
	(0.05)	(0.05)
Constant	0.73***	2.22***
	(0.03)	(0.60)
Controls	No	Yes
R-squared	0.00	0.12
N	101	101

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. OLS regression (0 is lower bound, 1 is upper bound). Dependent variable equals average share of individual contributions to the common account. Controls include all variables listed in appendix table C9. Unit of observation is the group playing the public goods game.

Table 4.9: Learning and Adoption of CDI Technologies by Leader/Decision-Making Engagement

	Leaders			Nonleaders
	(1)	(2)	(3)	(4)
	Knowledge	Knowledge	Adoption	Adoption
Leader Attended CDI Training	0.918***	0.987***	-0.167	-0.040
	(0.318)	(0.312)	(0.262)	(0.106)
Leader Speaks with CDI	0.019	-0.376	0.187	0.357***
	(0.314)	(0.481)	(0.259)	(0.103)
Leader's Adoption Plans				-0.104
				(0.137)
Decision-Making:				
Mix	-0.255		0.302	-0.046
	(0.445)		(0.381)	(0.186)
Consult	0.993**	0.751	0.953**	-0.188
	(0.468)	(0.543)	(0.408)	(0.220)
Mix × Leader Speaks with CDI		-		
		-		
Consult × Leader Speaks with CDI		0.635		
		(0.618)		
Mix × Leader's Adoption				0.144
				(0.229)
Consult × Leader's Adoption				0.346*
				(0.189)
Constant	2.000***	2.122***	0.301	0.136
	(0.416)	(0.425)	(0.367)	(0.144)
[.5em] District FE	Yes	Yes	Yes	Yes
N	37	37	37	35

In columns 1 and 2, the dependent variable sums the number of correct answers provided by club leaders for the 10 most novel facts introduced to farmers by CDI. In column 3, the dependent variable sums the number of novel production methods the club leader plans to adopt in the next season (out of the 6 most novel technologies introduced). Column 4 provides the non-leader average for the same variable as in column 3. Column 4 interacts the club's decision-making process with the dependent variable of column 3 (Leader: Adoption). 'Leader: Training' indicates the club leader attended a CDI training. 'Leader: Speak with CDI' indicates the leader has spoken to the CDI field agent in the past year. The omitted decision-making process category is 'Authoritarian.' Estimated using tobit with a lower bound of 0.

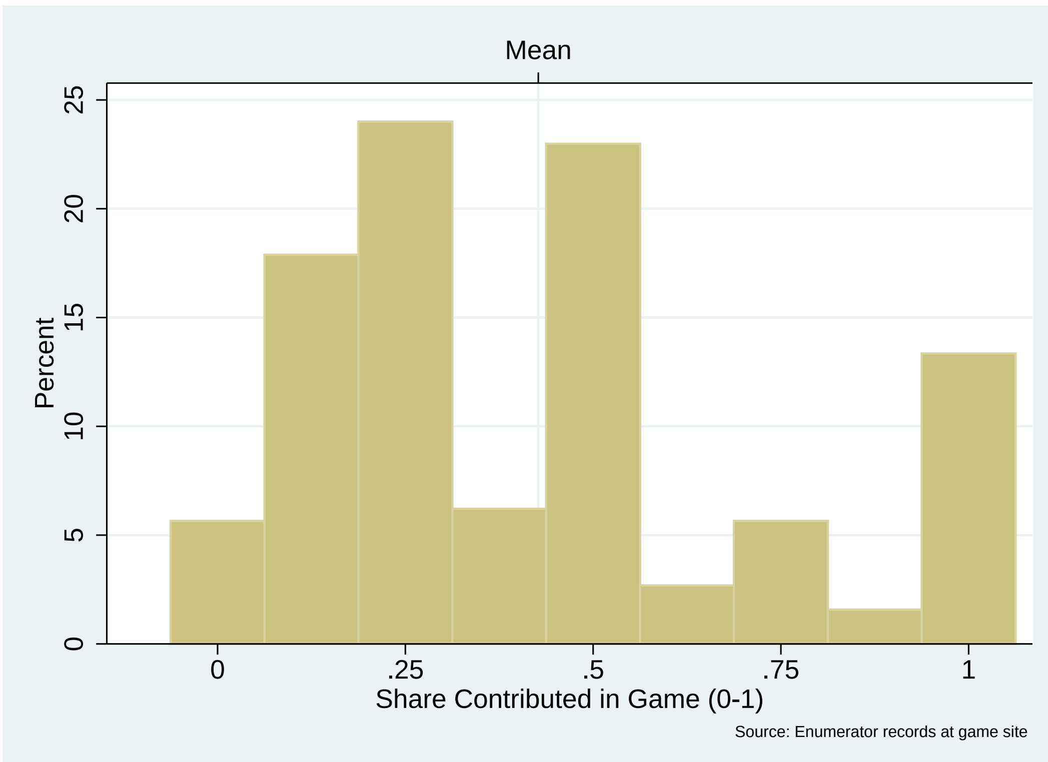

FIGURE 4.2: Histogram of Individual Contributions to Public Goods

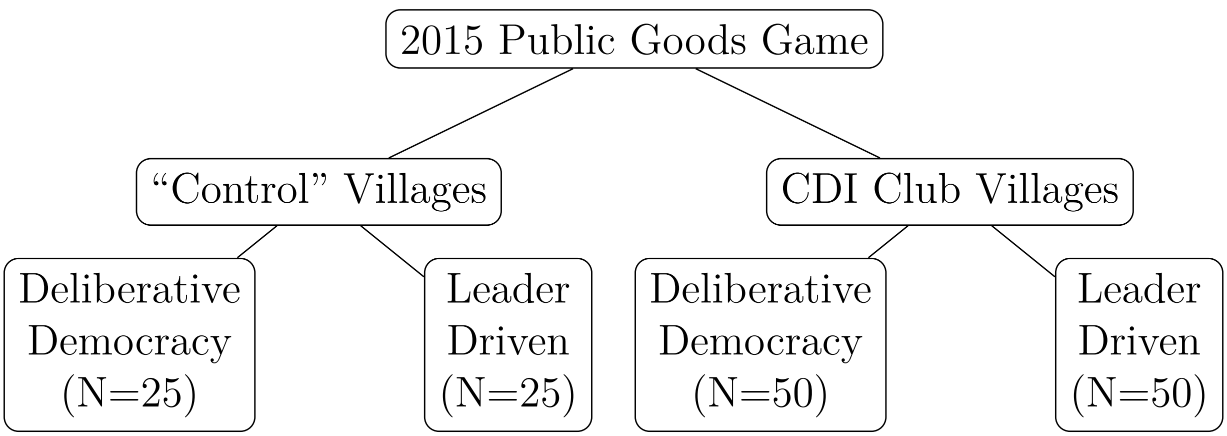

Figure 4.3: 2015 Public Goods Game Randomization

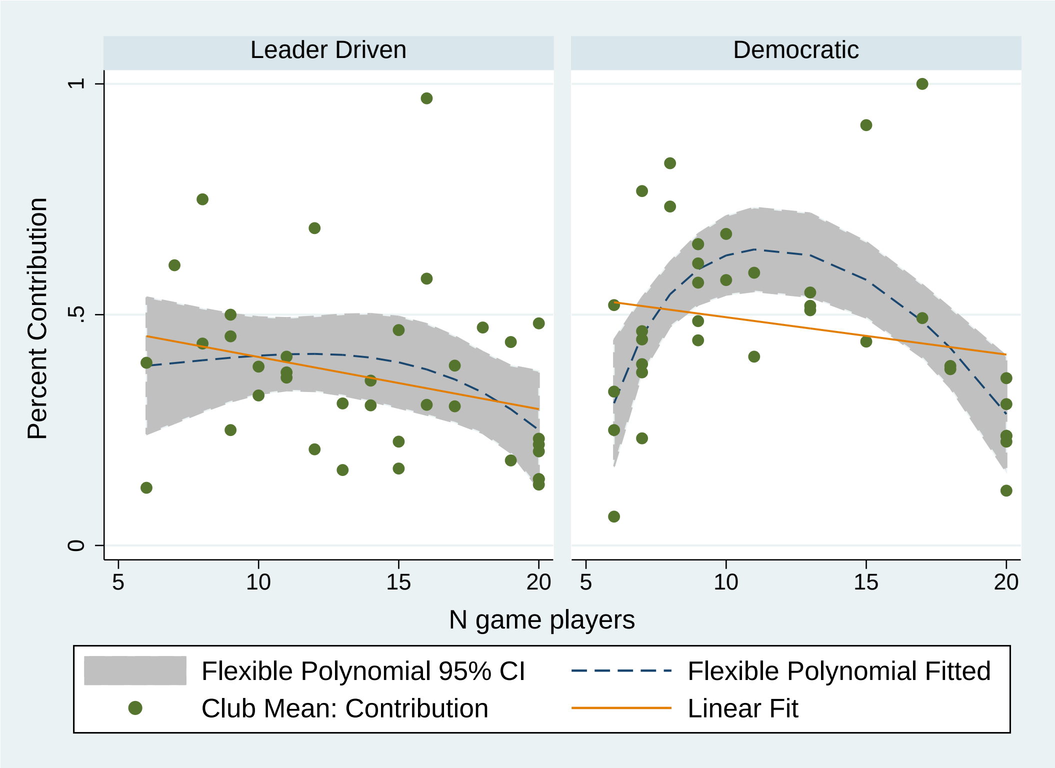

FIGURE 4.4: Average Club Level Contribution by Club Size and Decision-Making

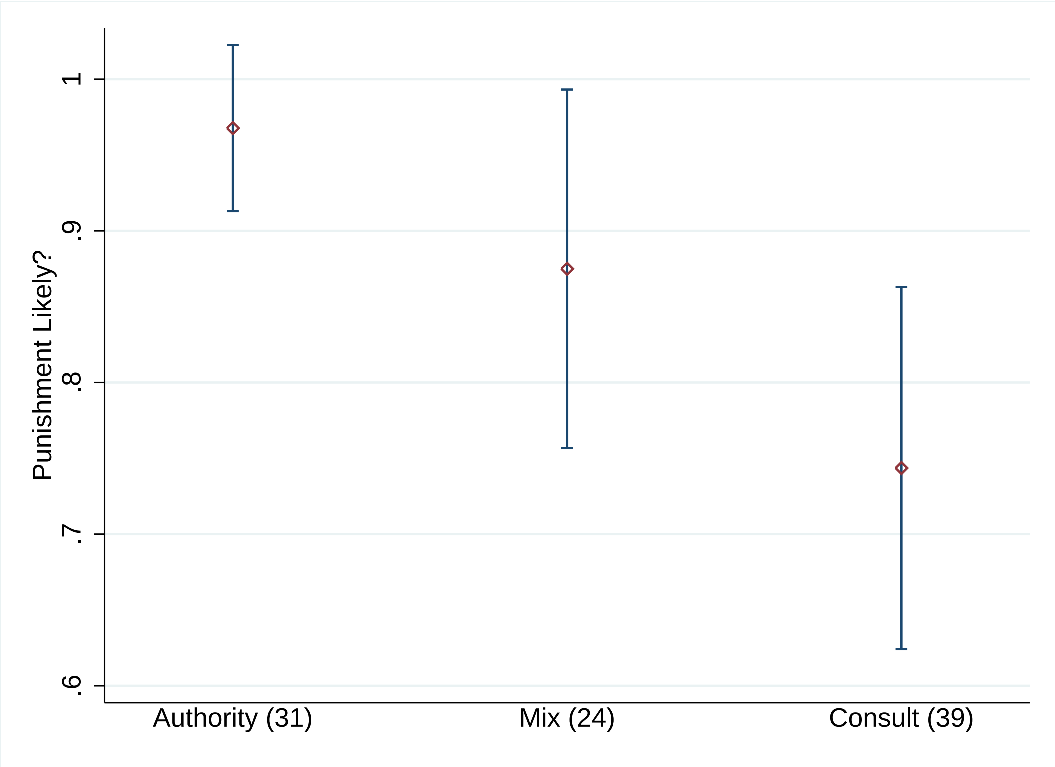

Figure 4.5: Punishment Likelihood by Decision-Making

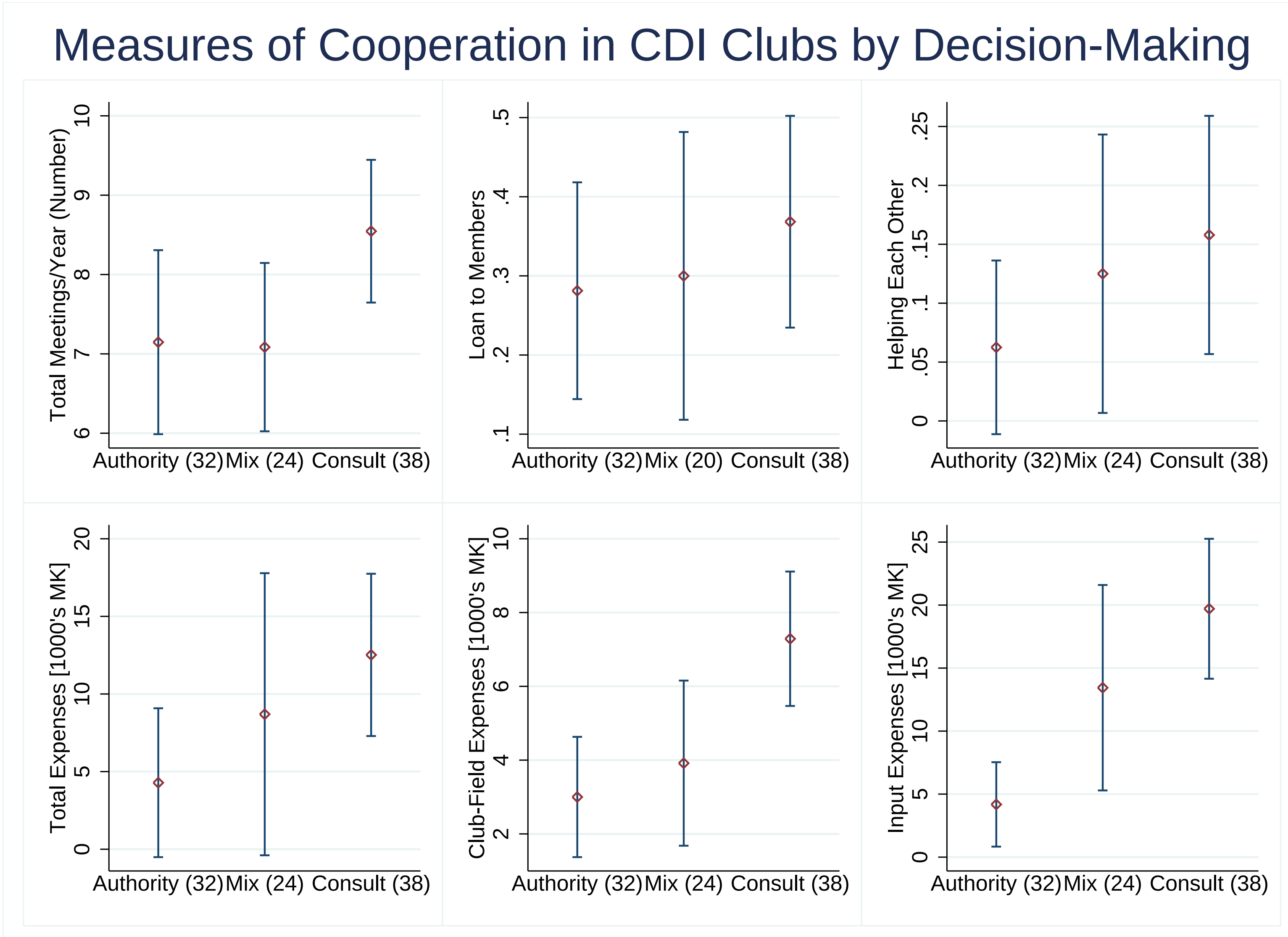

Figure 4.6: Measures of Club Effectiveness by Decision-Making

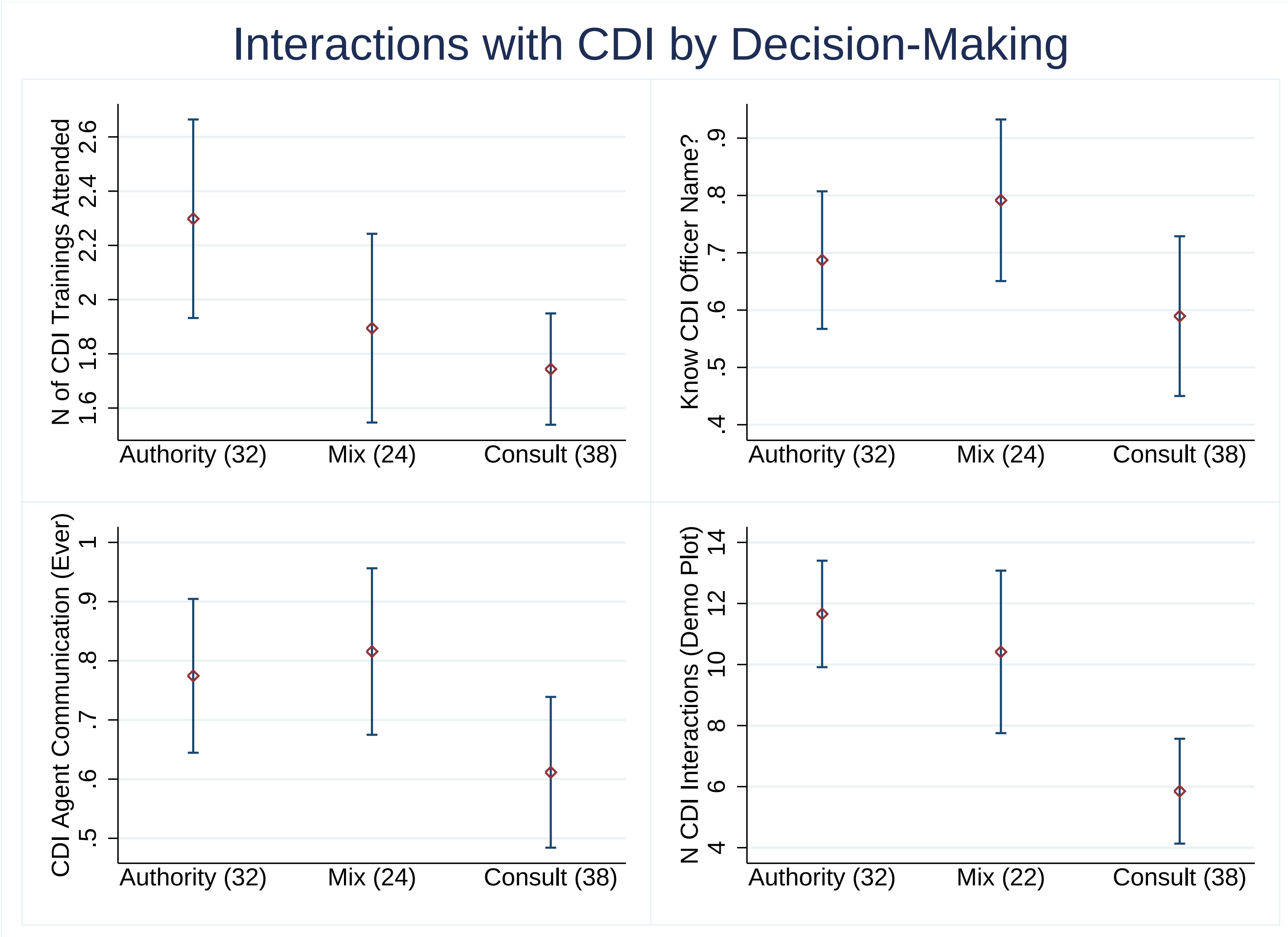

FIGURE 4.7: Measures of CDI Interactions by Decision-Making

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APPENDIX A

MULTI-OBJECT SOCIAL LEARNING AND TECHNOLOGY ADOPTION IN GHANA: DISTINGUISHING BELIEFS FROM KNOWLEDGE

A.1 Mathematical Appendix

A.1.1 Model Derivations and Proofs

Expected Profit Derivation

$$\mathbb{E}[\pi] = \mathbb{E}[(L-A)y^{TV} + y^{NV}(A) - e]$$

$$\Rightarrow \mathbb{E}[\pi] = (L-A)y^{TV} + A\mu(q) + \mathbb{E}[A^2(\theta - \tilde{\theta})^2] - e$$

$$\Rightarrow \mathbb{E}[\pi] = (L-A)y^{TV} + A\mu(q) + \mathbb{E}[A^2(\theta - \theta^* - \mu_\eta)^2] - e$$

$$\text{Recall, } \theta = \mathbb{E}[\theta^*] \text{ at the optimum:}$$

$$\Rightarrow \mathbb{E}[\pi] = (L-A)y^{TV} + A\mu(q) + \mathbb{E}[A^2(\mathbb{E}[\theta^*] - \theta^* - \mu_\eta)^2] - e$$

$$\Rightarrow \mathbb{E}[\pi] = (L-A)y^{TV} + A\mu(q) + \mathbb{E}[A^2(\mathbb{E}[\theta^*]^2 - 2\mathbb{E}[\theta^*]\theta^* - 2\mathbb{E}[\theta^*]\mu_\eta - 2\theta^*\mu_\eta + (\theta^*)^2 + \mu_\eta^2)] - e$$

$$\Rightarrow \mathbb{E}[\pi] = (L-A)y^{TV} + A\mu(q) + -e$$

$$A^2(\mathbb{E}[\theta^*]^2 - 2\mathbb{E}[\mathbb{E}[\theta^*]\theta^*] - 2\mathbb{E}[\mathbb{E}[\theta^*]\mu_\eta] - 2\mathbb{E}[\theta^*\mu_\eta] + \mathbb{E}[(\theta^*)^2] + \mathbb{E}[\mu_\eta^2]) - e$$

$$\Rightarrow \mathbb{E}[\pi] = (L-A)y^{TV} + A\mu(q) + A^2(\mathbb{E}[(\theta^*)^2] - \mathbb{E}[\theta^*]^2 + \mathbb{E}[\mu_\eta^2]) - e$$

$$\Rightarrow \mathbb{E}[\pi] = (L-A)y^{TV} + A\mu(q) + A^2(\sigma_\theta^2(e) + \sigma_\eta^2) - e$$

Formal Discussion and proof of Proposition 1

To facilitate analysis of proposition 1, I first define conditions under which ($a = 1, e = \bar{e}$) and ($a = 1, e = 0$) are feasible outcomes:

Definition 1 (Feasible Adoption With and Without Learning Effort) *If $A^*(\mu(q), \bar{e}) < \bar{A}$, then $\mu(q) < 2\gamma(\bar{e})\bar{A} + y^{TV} = \bar{A}^{LE}$ and adoption with learning effort* *is **not feasible**; i.e. the farmer will not choose* $(a = 1, e = \bar{e})$. *Otherwise, it will be feasible and it is possible for the farmer to choose this option. Likewise, if* $A^*(\mu(q), 0) < \bar{A}$, *then* $\mu(q) < 2\gamma(0)\bar{A} + y^{TV} = \bar{A}^{NE}$ *and adoption without learning effort is **not feasible**; otherwise, it is feasible.*

Proposition 1 (Characterizing Criteria for Adopting a New Crop) *Consider the case in which* $\bar{A}^{NE} < L^{LE}$, *where* $L^{LE} = 2\gamma(\bar{e})L + y^{TV}$ *(consequently,* $L^{NE} = 2\gamma(0)L + y^{TV}$*).*[1] *The farmer's adoption decision,* $a = \{0, \bar{e}\}$, *can be fully characterized by the cost of learning effort,* $\bar{e}$, *and his beliefs regarding the profitability of the new crop,* $\mu(q)$, *in the following way:*

i. If adoption with learning effort is not feasible then, $(a = 0, e = 0)$. *Furthermore, if* $\mu(q) < 2\sqrt{\bar{e}\gamma(\bar{e})} + y^{TV}$ *and adoption without learning effort is not feasible, then* $a = 0$ *and* $e = 0$.

ii. If adoption without learning effort is feasible and $\mu(q) < 2\sqrt{\bar{e}\frac{\gamma(\bar{e})\gamma(0)}{\Delta\gamma}} + y^{TV} < L^{LE}$, *then* $a = 1$ *and* $e = 0$. *If adoption without learning effort is feasible and* $\mu(q) \geq L^{LE}$ *and* $\mu(q) \leq \frac{-L-(4\gamma(0))^{-1}\sqrt{\frac{L^2-\gamma(0)^{-1}L^2\gamma(e)-\gamma(0)^{-1}\bar{e}}{(4\gamma(0))^{-2}}}}{(2\gamma(0))^{-1}} + y^{TV}$ *then* $a = 1$ *and* $e = 0$.

iii. If adoption with learning is feasible and adoption without learning is not feasible and $\mu(q) \geq 2\sqrt{\bar{e}\gamma(\bar{e})} + y^{TV}$, *then* $a = 1$ *and* $e = \bar{e}$. *If adoption with learning is feasible and adoption without learning is feasible and* $L^{LE} \geq \mu(q) \geq 2\sqrt{\bar{e}\frac{\gamma(\bar{e})\gamma(0)}{\Delta\gamma}} + y^{TV}$, *then* $a = 1$ *and* $e = \bar{e}$. *Otherwise, if adoption with learning is feasible and adoption without learning is feasible and* $L^{NE} \geq \mu(q) > \frac{-L-(4\gamma(0))^{-1}\sqrt{\frac{L^2-\gamma(0)^{-1}L^2\gamma(e)-\gamma(0)^{-1}\bar{e}}{(4\gamma(0))^{-2}}}}{(2\gamma(0))^{-1}} + y^{TV} > L^{LE}$, *then* $a = 1$ *and* $e = \bar{e}$.

where $\Delta\gamma = \gamma(0) - \gamma(\bar{e})$.

[1] Notice, $\bar{A}^{LE} < \bar{A}^{NE} < L^{NE}$ and $\bar{A}^{LE} < L^{LE} < L^{NE}$ by definition. This condition says that, as $\mu(q)$ increases, adoption without learning becomes feasible before the farmer farms the new technology on all cultivable land with learning, which seems reasonable and places limits on the relationship between $\gamma(0)$ and $\gamma(e)$ such that $1 > \frac{\gamma(e)}{\gamma(0)} > \frac{\bar{A}}{L}$.

Proof. By definition of maximization notice that, for example, $\{a, e\} = \{0, 0\}$ is chosen iff $\mathbb{E}[\pi(\{a, e\} = \{0, 0\})] > \mathbb{E}[\pi(\{a, e\} = \{1, 0\})]$ and $\mathbb{E}[\pi(\{a, e\} = \{0, 0\})] > \mathbb{E}[\pi(\{a, e\} = \{1, \bar{e}\})]$ and $\mathbb{E}[\pi(\{a, e\} = \{0, 0\})] > \mathbb{E}[\pi(\{a, e\} = \{0, \bar{e}\})]$. I rule out the possibility of $\{a, e\} = \{0, \bar{e}\}$ being chosen in the following manner: Suppose $\{a, e\} = \{0, \bar{e}\}$ is chosen. Then, $L \cdot y^{TV} < L \cdot y^{TV} - e$, which is a contradiction and $\mathbb{E}[\pi(\{a, e\} = \{0, 0\})] > \mathbb{E}[\pi(\{a, e\} = \{0, \bar{e}\})]$ is always true. Thus, there are only three alternatives the farmer is choosing among. The proof concept will show that if one alternative is preferred to the other two choices, then it must be true that the parameter space is characterized by proposition 1.

First, consider the choice of $\{a, e\} = \{0, 0\}$ in part $i.$ of proposition 1. I approach this problem in two parts. First, if adoption with learning effort is not feasible, then it is easy to show that adoption without learning effort is also not feasible ($\frac{\mu(q) - y^{TV}}{\gamma(e)} > \frac{\mu(q) - y^{TV}}{\gamma(0)}$), thus $\{a, e\} = \{0, 0\}$ is chosen. In the second part I am interested in the case in which adoption with learning effort is feasible, but adoption without learning effort is not feasible. I want to show that $\mathbb{E}[\pi(\{a, e\} = \{0, 0\})] > \mathbb{E}[\pi(\{a, e\} = \{1, 0\})]$ and $\mathbb{E}[\pi(\{a, e\} = \{0, 0\})] > \mathbb{E}[\pi(\{a, e\} = \{1, \bar{e}\})]$ iff the parameter condition, $\mu(q) < 2\sqrt{\bar{e}\gamma(\bar{e})} + y^{TV}$, is met. $\{a, e\} = \{1, 0\}$ is not feasible, thus it will never be chosen. I remain with showing conditions that satisfy the second inequality. This requires that $(L - A^*(\mu(q), \bar{e})) \cdot y^{TV} + A^*(\mu(q), \bar{e})[\mu(q) - A^*(\mu(q), \bar{e})(\gamma(e))] - e < L \cdot y^{TV}$. Replacing $A^*(\mu(q), \bar{e})$ with $\frac{\mu(q) - y^{TV}}{\gamma(\bar{e})}$, simple algebra can show that under these conditions $\mu(q) < 2\sqrt{\bar{e}\gamma(\bar{e})} + y^{TV}$. This proves part i. in proposition 1.

Next, consider part $ii.$ of proposition 1, the choice of $\{a, e\} = \{1, 0\}$. This option is chosen iff $\mathbb{E}[\pi(\{a, e\} = \{1, 0\})] > \mathbb{E}[\pi(\{a, e\} = \{1, \bar{e}\})]$ and $\mathbb{E}[\pi(\{a, e\} = \{1, 0\})] > \mathbb{E}[\pi(\{a, e\} = \{0, 0\})]$. Notice that the latter inequality is equivalent to the statement that adoption without learning is feasible. Thus, I assume feasibility of adoption without learning throughout this section of the proof. The first inequality depends on whether beliefs, q, are such that $\mu(q)$ is greater than or less than L^{LE}, the corner solution of $A^* = L$ when the farmer applies learning effort. If I have an interior solution ($A^* = \frac{\mu(q) - y^{TV}}{\gamma(0)}$) then I follow similar steps as those above to show that the first inequality requires $\mu(q) < 2\sqrt{\frac{\bar{\gamma}(e)\gamma(0)}{\Delta\gamma}} + y^{TV}$, which satisfies the first clause in part *ii*. of the proposition. When $\mu(q) \geq L^{LE}$, the farmer would choose $A^* = L$ when applying learning effort. Thus, I need to know when such learning effort is too costly. Here, I compare $(L - A^*(\mu(q), 0)) \cdot y^{TV} + A^*(\mu(q), 0)[\mu(q) - A^*(\mu(q), 0)\gamma(0)] > L[\mu(q) - L \cdot \gamma(\bar{e})]$, which can be rewritten as a quadratic inequality in $\mu(q)$. The solution to this quadratic inequality corresponds to the term written out in parts *ii*. and *iii*. of proposition 1 (the second solution refers to ranges of $\mu(q) > L^{NE}$ which revert to corner solutions in which the farmer will choose $A^* = L$ and $e = 0$.). The reader can follow the same approach to demonstrate the parameter ranges described in part *iii*. of proposition 1. QED.

A.1.2 Long Form of Equation 2.7

$$
\begin{aligned}
\Delta q_{it} = & \sum_{j=1}^{N} G'_{ij}(q_{j,t-1} - q_{j,t-2})\mathbb{1}[D_j = t-1] \\
& + \sum_{j=1}^{N} G'_{ij}(q_{j,t-1} - q_{j,t-2})\mathbb{1}[T_j = t-1] \\
& + \sum_{j=1}^{N} G'_{ij}(q_{j,t-1} - q_{j,t-2})\mathbb{1}[T_j < t-1 < D_j] \\
& + \sum_{j=1}^{N} G'_{ij}(q_{j,t-1} - q_{j,t-2})\mathbb{1}[D_j < t-1] \\
& + \sum_{j=1}^{N} G'_{ij}\Delta q_{j,t-1}\mathbb{1}[t-1 < T_j < D_j]
\end{aligned}
$$

A.1.3 Conditions Referred To in Model Implication 7

Consider the case of a disadopter. Recall, the direct effect of peer disadoption on beliefs is reflected in the term $\mathbf{g'_i}[\mathbf{\Delta q_{t-1}} \cdot \mathbb{1}(\mathbf{D} = t-1)]$. Notice that for some j who is a WT and for whom $D_j = t-1$, i's perceptions of j's beliefs are $\Delta q_{jt-1} = \mathbb{E}[\bar{\mathbf{q}}_{\mathbf{D}}] - \mathbb{E}[\bar{\mathbf{q}}_{\mathbf{A}}] < 0$. For some k

who is a ST and for whom $D_k = t - 1$

$$\Delta q_{kt-1} = \lambda^{D_k - T_k} q_{kT_k} + (1 - \lambda^{D_k - T_k})\bar{q}_k - \lambda^{D_k - 1 - T_k} q_{kT_k} - (1 - \lambda^{D_k - 1 - T_k})\bar{q}_k$$

$$\Delta q_{kt-1} = \lambda^{D_k - T_k} q_{kT_k}(1 - \lambda^{-1}) + \bar{q}_k(\lambda^{D_k - T_k}(\lambda^{-1} - 1)) < 0$$

When placing equal weight on ST and WT beliefs, then the condition referred to in model implication 7 is that

$$\underbrace{\mathbb{E}[\bar{\mathbf{q}}_{\mathbf{D}}] - \mathbb{E}[\bar{\mathbf{q}}_{\mathbf{A}}]}_{<0} < \underbrace{\lambda^{D_k - T_k - 1}(\lambda - 1)}_{<0, > -1} \underbrace{(q_{iT} - \bar{q}_k)}_{>0},$$

which states that the change in i's perception of WT beliefs is larger in magnitude (absolute terms) than the change in k's beliefs muted by k's decay rate from q_{kT_k} to $\bar{q}_k$. Slow decay rates (small k) will cause the expression on the right hand side to decrease as the distance between D_k and T_k increases. In either case, if the expression on the left hand side is larger in absolute magnitude than $q_{iT} - \bar{q}_k$, then the inequality holds with certainty. Combined, this condition suggests it is reasonable that WT disadoption may induce greater change in i's beliefs than changes in ST beliefs. A similar, though weaker, argument can be made when examining the effect of WT adoption. It is a weaker argument because, wlog, $\mathbb{E}[\bar{\mathbf{q}}_{\mathbf{D}}] - \mathbb{E}[\bar{\mathbf{q}}_{\mathbf{A}}] < \mathbb{E}[\bar{\mathbf{q}}_{\mathbf{A}}] - \mathbb{E}[\bar{\mathbf{q}}_{\mathbf{N}}]$.

A.1.4 A Brief Discussion of the Relationship Between Learning about θ^* and Updating $\bar{q}$

Suppose that a farmer has decided that it is worthwhile to apply learning effort to refine his understanding of θ^*. It is reasonable to assume that a process whereby a farmer learns about θ^* will also help the farmer gain information about $\bar{q}$. One might model this by allowing a 'partial' DUP through which farmers learn about q. Recall, from equation 2.7, beliefs for a farmer who has not yet adopted pineapple ($0 < t < T_i$) equals

$$q_{it}(\mathbf{G}', \mathbf{q_{t-1}}|\mathbf{T}, \mathbf{D}) = \sum_{j=1}^{N}[G'_{ij}q_{j,t-1}] \text{ if } 0 < t \leq T_i.$$

I allow a farmer to learn the true profitability as he puts effort in learning effort towards the production process. Allow $0 < \tau < 1$ to be a weight that determines the farmers ability to learn the true profitability of the new variety after applying learning effort (i.e., a who separates socially-induced beliefs "researched" beliefs about true profitability has a value of τ approaching 1). Then,

$$q_{it}(\mathbf{G}', \mathbf{q_{t-1}}|\mathbf{T}, \mathbf{D}) = \begin{cases} \sum_{j=1}^{N}[G'_{ij}q_{j,t-1}] \text{ if } 0 < t \leq T_i \text{ and } e = 0 \\ (1-\tau)\sum_{j=1}^{N}[G'_{ij}q_{j,t-1}] + \tau\bar{q}_i \text{ if } 0 < t \leq T_i \text{ and } e = \bar{e}. \end{cases}$$

The second term suggests that farmers who apply learning effort are less motivated by peer influence than farmers who do not apply learning effort (the amount depends on the value of τ). Depending on whether $\bar{q}$ is greater than or less than $\sum_{j=1}^{N}[G'_{ij}q_{j,t-1}]$, the application of learning effort might increase or decrease profitability beliefs, q.

A.1.5 A Brief Discussion of the Decision to Dis-adopt

Lemma 1 *A disadopter, i, has lower profitability beliefs at time period D_i than at the time of adoption T_i. I.e., $q_{iT_i} > q_{iD_i}$.*

I intuitively describe why this might be the case. Suppose that q_{iT_i} and $\bar{e}_{iT_i}$ prompt farmer i to adopt the new variety at period T_i. Then, assume that learning cost is strictly monotonically decreasing following farmer i's period of adoption (reflecting the fact that farmer i can now learn from his own experience in addition to the learning opportunities that existed prior to his period of adoption). Farmer i disadopts when his period-specific optimal solution suggests that the new variety is no longer profitable in expectation. This only occurs when q_{it} *decreases* in each period following adoption, $t > T_i$. Notice that if i eventually disadopts ($D_i \neq \infty$), then q_{it} only decreases as t increases; i.e., $D_i > t > T_i \Rightarrow q_{iT_i} > \bar{q}_i$.

A.1.6 Log-likelihood Simplification

Note that in the discrete case,

$$\Pr(T_i = t) = P_{it} \prod_{j=1}^{t-1} (1 - P_{ij}) \tag{A.1}$$

and

$$\Pr(T_i > t) = \prod_{j=1}^{t} (1 - P_{ij}) \tag{A.2}$$

yielding the log-likelihood function

$$\log L = \sum_{i=1}^{n} \delta_i \log \{P_{it}/(1 - Pit)\} + \sum_{i=1}^{n} \sum_{j=1}^{t_i} \log(1 - P_{ij}) \tag{A.3}$$

A.2 Data Appendix

A.2.1 Inter-person link heterogeneity

Within villages, there is considerable inter-person heterogeneity in the number of within-sample links reported along each of the measures listed above. Table A1 displays individual-summed mean and standard deviations of link numbers by village. The average number of direct family links in village four is relatively large, but so is the standard deviation associated with this measure. Residents in villages 1, 2 and 3 seem to make up for the relatively low number of family members residing in the village by having more friendship links. Second, the length of relationships in village 1 and 4 are more long-standing than villages 2 and 3. Third, village 4 has a good deal more gift-giving relationships on average than either of the other villages. Finally, it is important to observe the large standard deviations associated with most of the measures reported in this table. There is a large degree of within-village heterogeneity of network size for all variables, which will be exploited in the ensuing analysis.

Table A1: Network Link Numbers by Village

	Village 1 (N = 155)		Village 2 (N = 148)		Village 3 (N = 129)		Village 4 (N = 138)		All Villages (N = 570)	
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
Relationship Type										
N direct family links	1.71	1.38	1.40	1.07	1.98	1.73	3.19	3.22	2.05	2.11
N extended family links	14.71	14.29	8.09	8.38	10.93	10.11	28.23	22.72	15.41	16.71
N village friends	77.23	28.28	80.57	30.68	82.51	41.21	69.25	32.38	77.36	33.45
How Long Have You Known this Person?										
N known ¡ 1 year	0.92	4.78	0.84	3.72	0.43	1.04	2.23	5.09	1.11	4.08
N known 1-5 years	9.18	20.39	8.55	16.42	14.75	19.02	10.47	19.84	10.59	19.08
N known 5-10 years	16.49	19.07	30.61	29.69	33.78	31.08	13.61	19.05	23.37	26.55
N known 10+ years*	67.05	40.57	50.07	37.06	46.47	38.46	74.36	42.84	59.75	41.30
Relationship Strength										
N not friends**	61.50	28.12	71.71	29.67	66.79	35.26	60.91	34.67	65.21	32.10
N weak ties	58.64	36.57	56.61	28.12	48.59	41.00	58.28	38.56	55.75	36.31
N strong ties	18.92	21.34	22.82	24.52	22.50	18.30	23.36	26.11	21.82	22.83
Frequency of Conversation										
N links daily conversations	44.67	35.57	56.53	35.23	58.70	44.30	44.72	42.94	50.94	39.88
N links occasional conversations	48.94	41.84	33.49	27.70	36.65	41.07	55.57	46.10	43.75	40.53
Gift-giving Relationships										
N mutual gift-giving links	29.72	26.43	21.18	21.47	23.06	21.62	42.99	33.65	29.21	27.52
N not gift-giving links	59.35	29.24	65.01	27.91	69.11	41.83	50.78	32.35	60.95	33.52

* This measure includes responses of those stating "all my life".

** This measure includes all individuals in the village "unknown" to the survey respondent.

A.2.2 Discussion of Link Endogeneity Concerns

One way to test for the role of pineapple farming in the establishment of strong friendship ties is to analyze the conditional correlation of pineapple farming in the formation of a strong friendship link. I present dyadic regression[2] results in appendix table A2 showing correlates of strong tie formation along the observable variables I use in the analysis. Pineapple farming is only a significant correlate of strong tie relationships, conditional on other observables, in village 4, the village with the lowest incidence of pineapple adoption. Furthermore, the only four correlates of strong tie relationships that are consistently of the same sign and statistically significant across the four villages are relatively more permanent individual characteristics such as sex, age, education and score on an English comprehension test. This suggests that the categorization of a friendship from strong to weak tie does not change drastically over time.

Appendix table A3 tests whether the absolute difference in the year of adoption and disadoption for a strong tie differs from the year of adoption and disadoption of a weak tie. Simple t-tests show that in village 1, the year of adoption between strong ties who have adopted pineapple is farther apart than weak ties[3]; the opposite trend seems to be the case in village 2. There is no significant difference in the year of adoption between strong and weak ties in villages 3 and 4. When characterizing relationship strength by frequency of conversation, there are no significant differences in the distance in adoption of pineapple according to relationship strength. It is possible that relationships were formed in the context of participation in pineapple training activities through businesses, ngo's and extension workers. If this is the case, than this aspect of friendship formation can be

[2]A dyadic regression examines the correlations of various observable variables on the formation of a link between two nodes. Following Fafchamps and Gubert [2007], I estimate a linear regression of the form $P(Y_{ij} = 1) = \mathbf{fi_1}|X_i - X_j| + \mathbf{fi_2}(X_i + X_j) + \epsilon_{ij}$.

[3]This contradicts the logic in the above paragraph that individuals form friendships characterized by strong ties because they both adopt pineapple.

controlled for using exogenous peer effects in equation 2.12.

This discussion convincingly suggests that the decision to form a strong (or weak) tie has little to do with the decision to adopt pineapple. If there is a dynamic process by which weak ties turn into strong ties, it does not seem to be influenced by the particular pineapple adoption decision. In an ideal case, the econometrician would have dynamic information on relationship strength over time; however, in the absence of such data, the extremely rich information provided in the network module of this study is certainly a second-best option. Recall that though there is likely to be migration in and out of these villages, over 80% of households that participated in a survey in the late 90's[4] were located again in 2009. This suggests that many of the friendships are formed in early childhood or adolescence - villagers are likely to have known each other for a very long time. Thus, the analysis will interpret the responses of farmers regarding relationship strength in a manner consistent with the interpretation provided by the model in section 2.2.

[4]Before the peak of pineapple adoption.

Table A2: Dyadic Regression of Correlates of Strong Friendship Ties

	Village 1		Village 2		Village 3		Village 4	
Absolute Differences: $\lvert x_i - x_j \rvert$								
Ever Farmed Pineapple	-0.0083	(0.0080)	-0.0039	(0.0112)	0.0015	(0.0106)	-0.043**	(0.0199)
Sex	-0.062***	(0.0095)	-0.060***	(0.0127)	-0.098***	(0.0148)	-0.086***	(0.0149)
Age	-0.0020***	(0.0008)	-0.0034***	(0.0008)	-0.0022***	(0.0006)	-0.0020***	(0.0006)
Highest School Attended	-0.031**	(0.0123)	-0.014	(0.0127)	-0.0048	(0.0093)	-0.0048	(0.0114)
English Score	-0.0050**	(0.0022)	-0.00099	(0.0021)	-0.0029	(0.0019)	-0.0045**	(0.0021)
Mathscore	0.0030	(0.0039)	-0.0022	(0.0035)	0.0012	(0.0029)	0.0025	(0.0029)
Subjective Risk	-0.012***	(0.0038)	0.0067*	(0.0041)	-0.0028	(0.0038)	-0.0023	(0.0031)
Trained by Ext.	-0.080**	(0.0356)	0.014	(0.0173)	-0.019	(0.0280)	0.018	(0.0346)
Trained by Bus.	-	-	-0.028	(0.0217)	-0.0077	(0.0320)	-	-
Trained by NGO	-	-	0.065**	(0.0256)	-0.093**	(0.0467)	-	-
Sums: $x_i + x_j$								
Ever Farmed Pineapple	-0.040*	(0.0229)	0.023	(0.0237)	-0.023	(0.0239)	0.11**	(0.0407)
Sex	0.041	(0.0263)	-0.0047	(0.0260)	0.026	(0.0260)	0.0097	(0.0198)
Age	-0.00022	(0.0009)	0.0022***	(0.0008)	0.0012	(0.0008)	-0.0019**	(0.0008)
Highest School Attended	0.021*	(0.0110)	0.014	(0.0167)	0.0083	(0.0107)	0.019	(0.0130)
English Score	0.0014	(0.0035)	-0.0071*	(0.0038)	0.0048*	(0.0025)	0.000023	(0.0036)
Mathscore	-0.0029	(0.0046)	0.0097*	(0.0051)	-0.0033	(0.0033)	0.0015	(0.0035)
Subjective Risk	-0.0045	(0.0049)	-0.013**	(0.0055)	-0.0018	(0.0043)	0.0097*	(0.0056)
Trained by Ext.	0.19***	(0.0578)	-0.068	(0.0461)	0.053*	(0.0293)	-0.14***	(0.0410)
Trained by Bus.	-	-	-0.0066	(0.0368)	0.025	(0.0340)	-	-
Trained by NGO	-	-	-0.011	(0.0908)	0.20***	(0.0583)	-	-
Constant	0.27**	(0.1130)	0.24*	(0.1408)	0.13	(0.1194)	0.15	(0.1148)
Adj. R-squared	0.049		0.064		0.044		0.055	
N	6993		7300		5214		4037	

Note: Residents of villages 1 and 4 did not report being trained in pineapple cultivation by business or NGO relations.

Standard errors in parentheses clustered by individual

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A3: T-tests of Absolute Difference between i and j of Year of Pineapple Adoption and Disadoption by Strength of Tie

	Friendship Strength			Conversation Frequency		
Variable	WT	ST	Diff	Daily	Occ.	Diff
Village 1						
Year of Pineapple Adoption	7.63	9.14	1.51***	7.55	8.25	0.71
Year Ended Farming Pineapple	5.27	6.71	1.43**	5.08	5.82	0.74
Village 2						
Year of Pineapple Adoption	6.20	5.59	-0.62***	6.16	5.97	-0.19
Year Ended Farming Pineapple	2.06	2.60	0.54**	1.76	2.46	0.71***
Village 3						
Year of Pineapple Adoption	6.93	6.74	-0.19	6.80	6.96	0.16
Year Ended Farming Pineapple	2.53	2.44	-0.09	1.75	3.11	1.37***
Village 4						
Year of Pineapple Adoption	13.15	13.91	0.75	13.94	12.78	-1.16
Year Ended Farming Pineapple	12.77	13.47	0.70	13.50	12.42	-1.08

Table A4: Placebo test of profitability-belief variables interacted with I =Post 2004

		No Ctxt.	Ctxt. Effects
Belief-Updating ($\mathbf{g'_{k,it}}$):			
Share ST Adopters ($\mathbf{g'_{ST,it}} \cdot \mathbf{a_{t-1}}$)	γ^a_{ST}, (+)	-0.006	0.007
		(0.028)	(0.029)
Share ST Disadopters ($\mathbf{g'_{ST,it}} \cdot \mathbf{d_{t-1}}$)	γ^d_{ST}, (-)	0.018	0.020
		(0.035)	(0.042)
Share WT Adopters ($\mathbf{g'_{WT,it}} \cdot \mathbf{a_{t-1}}$)	γ^a_{WT}, (+++)	0.048*	0.044
		(0.028)	(0.029)
Share WT Disadopters ($\mathbf{g'_{WT,it}} \cdot \mathbf{d_{t-1}}$)	γ^d_{WT}, (- - -)	-0.093	-0.117*
		(0.063)	(0.065)
Belief-Updating Placebo Tests:			
Share ST Adopters ($\mathbf{g'_{ST,it}} \cdot \mathbf{a_{t-1}}$) $\times$ Post 2004	$\gamma^a_{ST,I}$, (0)	0.067	0.063
		(0.048)	(0.049)
Share ST Disadopters ($\mathbf{g'_{ST,it}} \cdot \mathbf{d_{t-1}}$) $\times$ Post 2004	$\gamma^d_{ST,I}$, (0)	-0.042	-0.042
		(0.041)	(0.044)
Share WT Adopters ($\mathbf{g'_{WT,it}} \cdot \mathbf{a_{t-1}}$) $\times$ Post 2004	$\gamma^a_{WT,I}$, (0)	-0.009	-0.009
		(0.042)	(0.043)
Share WT Disadopters ($\mathbf{g'_{WT,it}} \cdot \mathbf{d_{t-1}}$) $\times$ Post 2004	$\gamma^d_{WT,I}$, (0)	-0.004	0.007
		(0.069)	(0.071)
Learning ($\mathbf{g_{k,it}} \cdot S^k_{it}$)	$\boldsymbol{\rho}$	Yes	Yes
Family Effects	$\boldsymbol{\phi}$	Yes	Yes
Controls	β	Yes	Yes
Contextual Effects	$\boldsymbol{\delta}$	No	Yes
Correlated Effects	α_t and ν_v	Yes	Yes
R-squared		0.05	0.06
Clusters		482.00	482.00
N		9946.00	9946.00

$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. OLS estimation of modified equation 2.16 when data are inputed to maximize equation 2.15. I modify equation 2.16 by adding interaction term I in front of the belief variables as a placebo test. Beliefs dynamics should not differ significantly based on whether the new crop is profitable or not (peer behavior still helps determine profitability beliefs). See description in table 2.7 for a description of variables under the full specifications with and without contextual effects (columns 2 and 5). Null hypothesis tests of $\boldsymbol{\gamma}$ cannot be rejected.

Table A5: Do peers influence the decision to disadopt?

		Pre 2004	Post 2003	All
Strong Ties:				
Number Experienced ST (S_{it}^{ST})	ρ_{ST}	-0.003	-0.005	-0.000
		(0.002)	(0.004)	(0.002)
Share ST Adopters ($\mathbf{g'_{ST,it}} \cdot \mathbf{a_{t-1}}$)	γ_{ST}^{a}	0.008	-0.105	-0.035
		(0.076)	(0.090)	(0.048)
Share ST Disadopters ($\mathbf{g'_{ST,it}} \cdot \mathbf{d_{t-1}}$)	γ_{ST}^{d}	0.024	0.035	0.020
		(0.263)	(0.177)	(0.122)
Weak Ties:				
Number Experienced WT (S_{it}^{WT})	ρ_{WT}	-0.000	-0.004	-0.001
		(0.001)	(0.002)	(0.001)
Share WT Adopters ($\mathbf{g'_{WT,it}} \cdot \mathbf{a_{t-1}}$)	γ_{WT}^{a}	-0.057	-0.122	-0.064
		(0.089)	(0.137)	(0.079)
Share WT Disadopters ($\mathbf{g'_{WT,it}} \cdot \mathbf{d_{t-1}}$)	γ_{WT}^{d}	-0.039	-0.313	-0.177
		(0.229)	(0.224)	(0.148)
Family:				
Total DF in Village ($N_{DF,it}$)	ϕ_{DF}	-0.006	-0.164***	-0.051**
		(0.027)	(0.049)	(0.024)
Share DF Adopters ($\mathbf{g'_{DF,it}} \cdot \mathbf{a_{t-1}}$)	γ_{DF}^{a}	-0.027	0.064	0.005
		(0.053)	(0.089)	(0.043)
Share DF Disadopters ($\mathbf{g'_{DF,it}} \cdot \mathbf{d_{t-1}}$)	γ_{DF}^{d}	0.196	-0.000	-0.007
		(0.161)	(0.139)	(0.090)
Controls	β	Yes	Yes	Yes
Contextual Effects	**ffi**	Yes	Yes	Yes
Correlated Effects	α_t and ν_v	Yes	Yes	Yes
R-squared		0.23	0.28	0.18
Clusters		167	177	211
N		1070	746	1816

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Analysis of the decision to disadopt in analogous manner to hazard model of adoption. Dependent variable equals 0 when farmer begins cultivating pineapple and equals 1 when he exits pineapple cultivation (Those who do not disadopt during the analyzed period are censored). OLS estimation of equation 2.16 when data are inputed to maximize equation 2.15. Significantly, peer experiences with pineapple do not seem to influence the decision to disadopt. Farmers with larger numbers of direct family members who head households in the village decrease the probability of disadoption, especially after the market crash, which is consistent with the idea that risk-sharing networks are better able to absorbe negative shocks thereby prolonging the period of pineapple cultivation.

Table A6: Mixed Effect Model

		(1)	
Within Effects:			
Within: Share ST Adopters ($\mathbf{g'_{ST,it}} \cdot \mathbf{a_{t-1}}$)	B: γ^a_{ST}, (+)	0.028	(0.027)
Within: Share ST Disadopters ($\mathbf{g'_{ST,it}} \cdot \mathbf{d_{t-1}}$)	B: γ^d_{ST}, (-)	0.106*	(0.060)
Within: Share WT Adopters ($\mathbf{g'_{WT,it}} \cdot \mathbf{a_{t-1}}$)	B: γ^a_{WT}, (+++)	0.076**	(0.032)
Within: Share WT Disadopters ($\mathbf{g'_{WT,it}} \cdot \mathbf{d_{t-1}}$)	B: γ^d_{WT}, (- - -)	-0.017	(0.077)
Within: Number Experienced ST (S^{ST}_{it})	B: ρ_{ST}, (+++)	0.010***	(0.001)
Within: Number Experienced WT (S^{WT}_{it})	B: ρ_{WT}, (+)	0.001*	(0.001)
Between Effects:			
Between: Share ST Adopters ($\mathbf{g'_{ST,it}} \cdot \mathbf{a_{t-1}}$)	W: γ^a_{ST}, (+)	0.007	(0.027)
Between: Share ST Disadopters ($\mathbf{g'_{ST,it}} \cdot \mathbf{d_{t-1}}$)	W: γ^d_{ST}, (-)	-0.019	(0.037)
Between: Share WT Adopters ($\mathbf{g'_{WT,it}} \cdot \mathbf{a_{t-1}}$)	W: γ^a_{WT}, (+++)	0.082**	(0.032)
Between: Share WT Disadopters ($\mathbf{g'_{WT,it}} \cdot \mathbf{d_{t-1}}$)	W: γ^d_{WT}, (- - -)	-0.219***	(0.065)
Between: Number Experienced ST (S^{ST}_{it})	W: ρ_{ST}, (+++)	-0.001	(0.002)
Between: Number Experienced WT (S^{WT}_{it})	W: ρ_{WT}, (+)	-0.002**	(0.001)
Time-Varying Controls	β, **ffi**	Yes	
Clusters		423	
N		7582	

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Analysis restricted to pre-market shock period (prior to 2004). Results of a linear mixed effect model splitting the effects of individual-varying covariates on the probability of adoption into within-individual and between-individual effects. Hypothesized results associated with movements in beliefs over yield are stronger in the **between** coefficients. Results associated with gaining production knowledge are stronger in **within** coefficients. This supports a narrative in which those with the lowest beliefs have the highest disadopters on average whereas those most likely to adopt by gaining production knowledge have more opportunities to learn in any given period than others.

APPENDIX B

ALTRUISM AND INSURANCE IN COSTLY SOLIDARITY NETWORKS

B.1 Adding a Sequence of History-dependent Nash Equilibria (SHDNE) Transfers to Our Model

Households can default to an SHDNE (instead of a no-transfer equilibria) and transfer amounts in such settings will depend on the level of altruism between household 1 and 2 and the number of household 1's outstanding gift-commitments. The SHDNE transfer, $\tau^D(h_t)$, given history h_t is

$$\tau^D(h_t) = \begin{cases} r \text{ s.t. } u_1'(y_1(s_t) - r)/u_2'(y_2(s_t) + r) = \gamma_1(g_1(h_t)) \\ \qquad \text{if } u_1'(y_1(s_t))/u_2'(y_2(s_t)) < \gamma_1(g_1(h_t)) \\ r \text{ s.t. } u_1'(y_1(s_t) - r)/u_2'(y_2(s_t) + r) = 1/\gamma_2(g_1(h_t)) \\ \qquad \text{if } u_1'(y_1(s_t))/u_2'(y_2(s_t)) > 1/\gamma_2(g_1(h_t)) \\ 0 \text{ otherwise.} \end{cases} \tag{B.1}$$

In other words, 1 will transfer to 2 when 2's marginal utility of consumption at his state-specific income level is high enough relative to individual 1's history-dependent gift-network size. Similarly 2's transfers to 1 will depend on 2's history-dependent gift-network size. In either case, the SHDNE transfer is voluntary and not contingent on any requirement for the recipient party to reciprocate in a future period.

To set up the household's problem with default to SHDNE transfers after history h_t,

$U_1(h_t)$ can be re-written in the following manner:

$$
\begin{aligned}
U_1(h_t) = \quad & u_1(y_1(s_t) - \tau(h_t)) - u_1(y_1(s_t) - \tau^D(h_t)) \\
& + \gamma_1(g_1(h_t))u_2(y_2(s_t) + \tau(h_t)) - \gamma_1(g_1(h_t))u_2(y_2(s_t) + \tau^D(h_t)) \\
& + \mathbb{E} \sum_{k=t+1}^{\infty} \delta^{k-t} \left\{ \begin{array}{l} u_1(y_1(s_k) - \tau(h_k)) - u_1(y_1(s_k) - \tau^D(h_t)) \\ +\gamma_1(g_1(h_t))u_2(y_2(s_k) - \tau(h_k)) - \gamma_1(g(h_t))u_2(y_2(s_k) - \tau^D(h_t)) \end{array} \right\} \\
& - \alpha_1(g_1^D(h_t))
\end{aligned}
\tag{B.2}
$$

where instead of only receiving income $y_1(s_t)$ in each period after h_t, household 1 will subtract net SHDNE transfers as well. The rest of the maximization problem is straightforward to compute once a functional form for utility is identified.

B.2 Appendix Tables

Table B1: Household Summary Statistics

	N	Mean	Sd	5 p-tile	95 p-tile
Fixed Over Time:					
HH size	606	5.09	2.23	2	9
Gift Network Size	597	9.94	10.10	0	31
Gifts and Loans (last 2 months):					
N Gifts Given	2,983	0.82	1.37	0	4
N Gifts Received	2,983	0.30	0.80	0	2
N Loans Given	2,983	0.16	0.51	0	1
N Loans Taken	2,983	0.07	0.29	0	1
Total Value of all Gifts Given	1,175	20.02	75.25	1	66
Total Value of all Gifts Received	542	12.58	35.75	1	35
Total Value of all Loans Given	362	57.00	113.25	5	200
Total Value of all Loans Taken	191	54.90	133.46	3	220
Food Consumption (last month):	**HH Head**	**Spouse**	**P-value**	**Total**	**SD**
PC Food Consumption	10.43	16.71	0	26.45	20.77
PC Purchased Food	3.11	15.86	0	19.42	18.83
PC Home-produced Food	7.78	1.60	0	8.63	7.98

Gift Network data missing for a subset of observations. N of loans/gifts given equal zero if none given/received. Value of gifts/loans contingent on having received at least one. Gift/loan data excludes within-household transfers and “Gifts Receives” and “Loans Taken” exclude all gifts or loans that originate outside of the study village. Household food consumption (total) sums the head of households and spouse’s response. P-value is t-test significance of difference in category of food spending between HH head and spouse.

Table B2: Lottery Winnings

Variables:	N	Mean	Sd
Own Lottery Winnings:			
Cash - Private	1,288	1.21	5.70
Cash - Public	1,288	1.12	5.52
Gift-Giving Network Average Lottery Winnings:			
Friends Cash-Private	1,184	1.17	1.64
Friends Cash-Public	1,184	1.16	1.45

Friend lottery winnings multiply the vector of lottery winners by the row-normalized gift network adjacency matrix (result is average friends' lottery winnings).

Table B3: Household Summary Statistics

	N Winners		Win-at-all		Win-Private		Win-Public	
	N-No	N-Win	Diff	P-Value	Diff	P-Value	Diff	P-Value
Fixed Over Time:								
HH size	190	119	0.31	0.22	0.56	0.06*	-0.04	0.91
N Mutual Gifts	190	119	-0.52	0.66	-0.78	0.57	0.24	0.86
Gifts and Loans (last 2 months):								
N Gifts Given	190	119	0.14	0.64	0.07	0.85	0.34	0.32
N Gifts Received	190	119	0.11	0.46	0.18	0.28	0.11	0.52
N Loans Given	190	119	0.08	0.45	-0.09	0.49	0.12	0.36
N Loans Taken	190	119	-0.05	0.32	-0.06	0.26	-0.00	0.95
Food Consumption (last month):								
PC Food Consumption	187	117	-0.75	0.79	-4.40	0.18	2.49	0.44
PC Purchased Food	187	117	-0.02	0.99	-1.97	0.49	2.04	0.47
PC Home-produced Food	187	117	-0.73	0.49	-2.43	0.05**	0.45	0.71

Balance test of round 1 observations. categorizes households according to those who won either lottery at any point during the course of the year (N-No, number of HH that did not win; N-Win, number of HH that did win). represents either lottery. represents those who only won private (public) lotteries. All P-Values represent two-tailed hypothesis tests (t-statistics).

Table B4: Gift Network = MMG

	No Interaction			Shut-down Hypothesis		
	(1)	(2)	(3)	(4)	(5)	(6)
N Mutual Gifts = 0	-0.488**	0.118	-0.396**	-0.491**	0.102	-0.398**
	(0.215)	(0.197)	(0.163)	(0.215)	(0.189)	(0.161)
N Mutual Gifts	0.050***	0.021***	0.020***	0.055***	0.023***	0.022***
	(0.008)	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)
Private Cash Winnings	0.085	0.038	0.062	0.047	-0.003	0.040
	(0.086)	(0.035)	(0.040)	(0.127)	(0.047)	(0.063)
Public Cash Winnings	0.179**	0.072	0.052	0.499***	0.200***	0.205**
	(0.086)	(0.046)	(0.051)	(0.127)	(0.066)	(0.080)
N Mutual Gifts × Private Cash Winnings				0.003	0.003	0.002
				(0.008)	(0.003)	(0.004)
N Mutual Gifts × Public Cash Winnings				-0.031***	-0.013***	-0.015***
				(0.009)	(0.005)	(0.005)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1645	1602	1645	1645	1602	1645

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Dependent Variable equals log of gifts given in columns 1 and 4, number of gifts given in column 2 and 5, and value per gift in columns 3 and 6. Village and Round Fixed Effects Included in Every Specification. Tobit regression in columns 1, 3, 4 and 6 with a lower bound of zero (no upper bound); poisson regression in columns 2 and 5.

TABLE B5: Dyadic Regressions - Pooled Base Test

	Pooled - HH FE		Pooled - TGT HH FE	
	Log(Amount$_{ijt}$)	Number$_{ijt}$	Log(Amount$_{ijt}$)	Number$_{ijt}$
Network Size$_i$			0.030	0.014
			(0.028)	(0.015)
Mutual Gift$_{ij}$			4.488***	2.380***
			(0.601)	(0.306)
Network Size$_i$ $\times$ Mutual Gift$_{ij}$			-0.047	-0.020
			(0.036)	(0.020)
Lottery-Private$_{it}$	0.486	0.255	0.211	0.065
	(0.434)	(0.238)	(0.284)	(0.156)
Lottery-Public$_{it}$	0.134	0.094	0.439**	0.297**
	(0.184)	(0.089)	(0.200)	(0.123)
Lottery-Private$_{it}$	-0.151**	-0.087**	-0.099***	-0.050**
$\times$ Network Size$_i$	(0.060)	(0.034)	(0.037)	(0.020)
Lottery-Public$_{it}$	-0.027	-0.019*	-0.033*	-0.026*
$\times$ Network Size$_i$	(0.018)	(0.010)	(0.019)	(0.014)
Lottery-Private$_{it}$	1.158**	0.462	0.525	0.306
$\times$ Mutual Gift$_{ij}$	(0.560)	(0.297)	(0.434)	(0.201)
Lottery-Public$_{it}$	1.279***	0.425*	0.093	-0.137
$\times$ Mutual Gift$_{ij}$	(0.420)	(0.244)	(0.374)	(0.194)
Lottery-Private$_{it}$	0.106*	0.072**	0.077*	0.045**
$\times$ Mutual Gift$_{ij}$ $\times$ Network Size$_i$	(0.062)	(0.035)	(0.039)	(0.020)
Lottery-Public$_{it}$	-0.004	0.008	0.011	0.016
$\times$ Mutual Gift$_{ij}$ $\times$ Network Size$_i$	(0.028)	(0.016)	(0.028)	(0.017)
TGT HH FE	No	No	Yes	Yes
HH FE	Yes	Yes	No	No
Village FE	No	No	No	No
Round FE	Yes	Yes	Yes	Yes
N	133975	130761	130761	130761

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable in odd columns equals amount of actual gift given from i to j in any given round t; Even columns equals number of gifts. 'Network Size$_i$' indicates household i's gift-network size (any type of gift-relation). Odd columns are tobits with lower bound of zero. Even columns are poisson regressions. Columns 1-2 only include links (i and j) with mutual gift-relations at baseline (actual gifts given during the 5 rounds). Columns 3-4 include all oher links (actual gifts given).

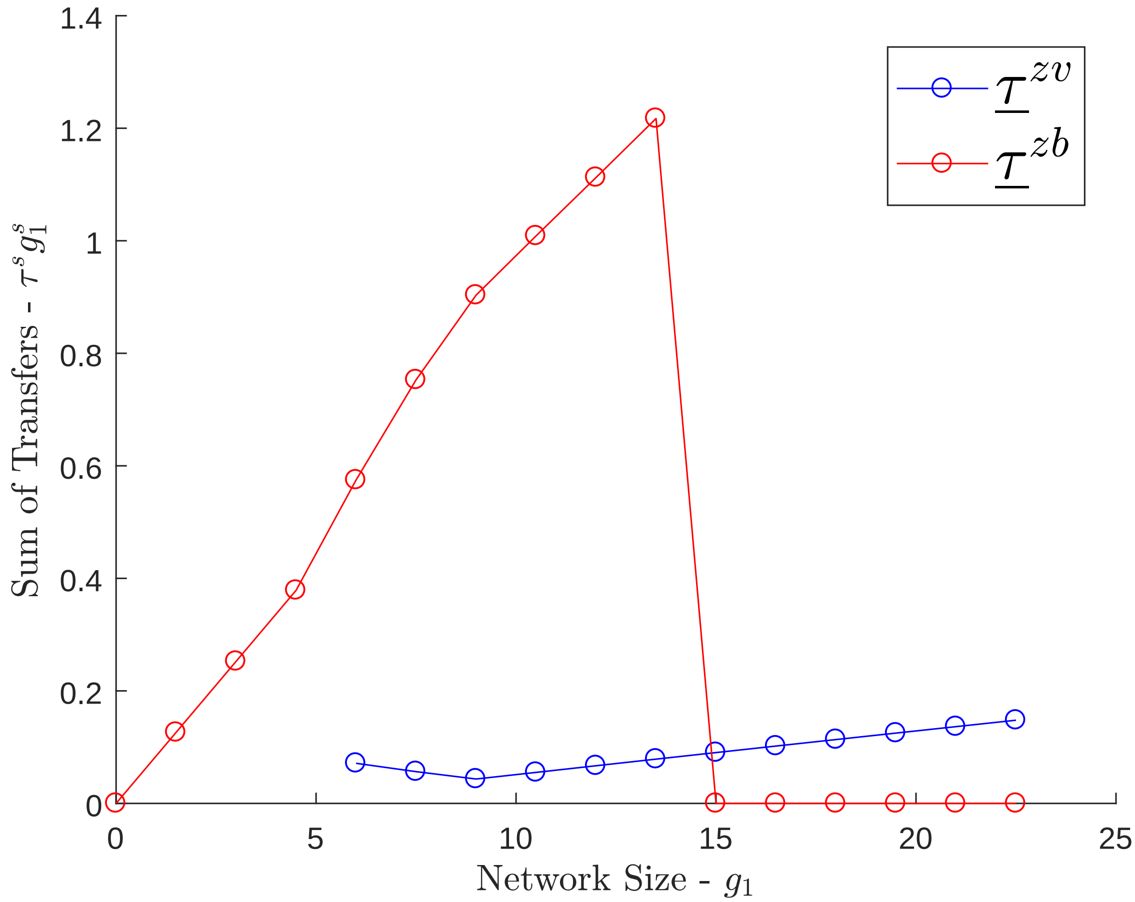
Table B6: Dyadic Regressions - Food Shocks

	Log($Amount_{ijt}$)	Log($Amount_{ijt}$)	$Number_{ijt}$	$Number_{ijt}$
Mutual $Gift_{ij}$	3.840^{***}	3.603^{***}	2.085^{***}	1.900^{***}
	(0.332)	(0.322)	(0.197)	(0.180)
Lottery-$Private_{it}$	-0.449^{*}	-0.473^{*}	-0.278^{*}	-0.287^{*}
	(0.248)	(0.260)	(0.145)	(0.148)
Lottery-$Public_{it}$	0.061	0.012	0.041	0.016
	(0.180)	(0.188)	(0.114)	(0.100)
Food-$Shock_{ijt}$	-0.063	-0.098	-0.055	-0.043
	(0.215)	(0.187)	(0.119)	(0.101)
Food-$Shock_{ijt}$	-0.155	-0.105	-0.054	-0.049
× Mutual $Gift_{ij}$	(0.313)	(0.262)	(0.161)	(0.125)
Gift-Network Interaction				
Lottery-$Private_{it}$	0.711^{**}	0.675^{**}	0.559^{***}	0.486^{***}
× Mutual $Gift_{ij}$	(0.335)	(0.318)	(0.170)	(0.161)
Lottery-$Public_{it}$	0.034	0.279	-0.071	0.045
× Mutual $Gift_{ij}$	(0.269)	(0.271)	(0.151)	(0.139)
Food-Shock Interaction				
Lottery-$Private_{it}$	-0.467^{*}	-0.560^{*}	-0.258^{**}	-0.295^{*}
× Food-$Shock_{ijt}$	(0.258)	(0.301)	(0.129)	(0.151)
Lottery-$Public_{it}$	0.494^{**}	0.623^{**}	0.247^{*}	0.309^{**}
× Food-$Shock_{ijt}$	(0.252)	(0.265)	(0.141)	(0.122)
Triple Interaction				
Lottery-$Private_{it}$	1.043^{***}	1.014^{***}	0.394^{***}	0.337^{*}
× Food-$Shock_{ijt}$ × Mutual $Gift_{ij}$	(0.312)	(0.381)	(0.138)	(0.190)
Lottery-$Public_{it}$	-0.792^{**}	-0.894^{*}	-0.337^{*}	-0.414^{*}
× Food-$Shock_{ijt}$ × Mutual $Gift_{ij}$	(0.350)	(0.476)	(0.177)	(0.236)
HHN FE	No	Yes	No	Yes
TGT HHN FE	Yes	No	Yes	No
Round FE	Yes	Yes	Yes	Yes
N	110721	110721	110721	110721

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dependent variable in columns 1-2 equals amount of actual gift given from i to j in any given round t; in columns 3-4 it equals number of gifts. 'Food-$Shock_{ijt}$' indicates the difference between i and j estimated food consumption residual ($\hat{\chi}_i - \hat{\chi}_j$ — household and round fixed effects). Columns 1-2 estimated using tobit estimator with lower bound on dependent variable of zero. Columns 3-4 use poisson estimator. 'Mutual $Gift_{ij}$' refers to the existence of reciprocal gift-relationships between i and j.

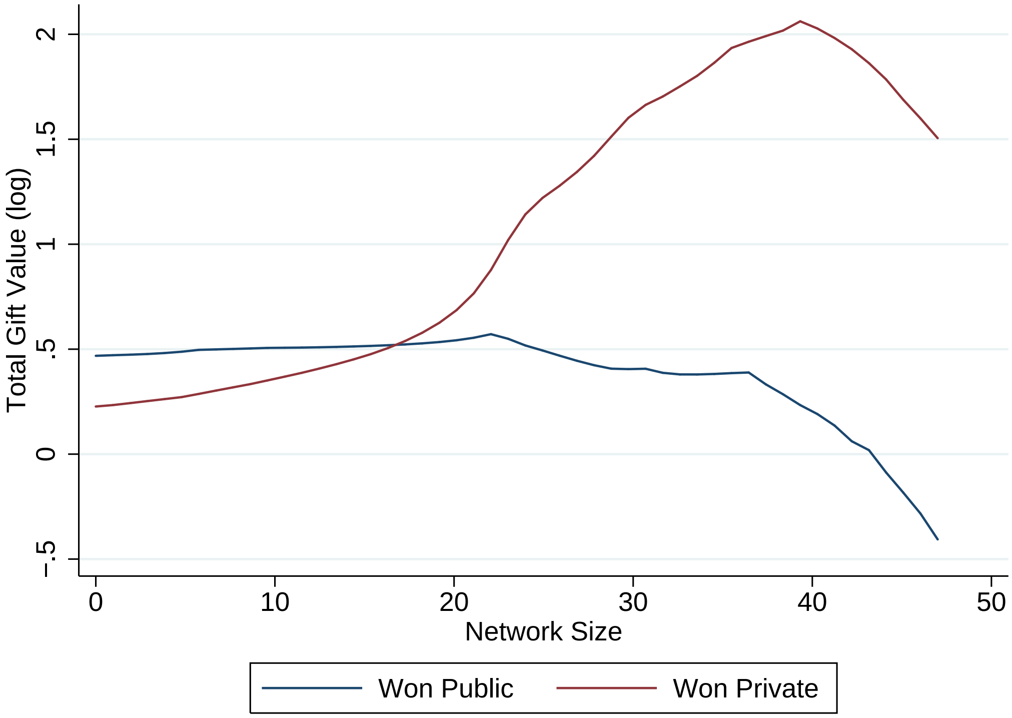
B.3 Appendix Figures

Figure B1: Amount of Total Transfers by Network Size



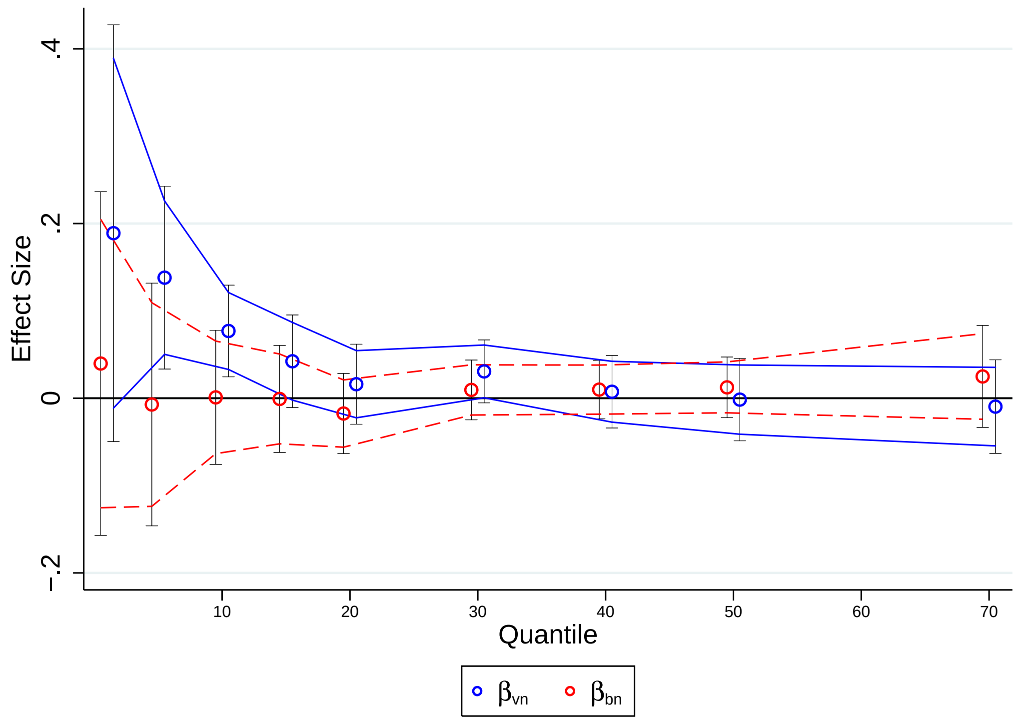
Note:

Figure B2: Local Polynomial Smoothing - Shut-down Hypothesis



Note: Values on the y-axis adjusted for household fixed effects. See description in figure 3.7

Figure B3: Results of Quantile Regression by Quantile - All Rounds



Note: Estimation of equation 3.15 using simultaneous quantile regression estimator (100 bootstrap repetitions). Dependent variable equals log per-capita food consumption. All rounds of data used. Blue represents average network treatment effect of privately revealed lottery winnings and red represents publicly revealed lottery winnings. Evaluated at the 1%, 5%, 10%, 15%, 20%, 30%, 40%, 50%, and 70%-tiles. Coefficient estimates offset relative to x-axis for ease of viewing.

APPENDIX C

COMMUNITY DRIVEN DEVELOPMENT SUFFERS FROM HOMOGENEOUS TREATMENT OF COMMUNITIES

C.1 Game Details

C.1.1 2014 Game Instructions

Before the game starts:

- Arrange to meet all the CDI club members in one central village location, secluded from the rest of the village as to avoid bystanders
- Place 400 KW in brown envelopes in notes of 50 KW (these cannot be see through), meaning 400 K per envelope, one envelop per club member.
- Place a table or mat in the center area. and arrange seating in a circle.

Once all the members are present, ask every individual to introduce themselves to the group by name. Note down who is present and who is not present on the next page. **A minimum of 6 members should be present to play the game**.

Read from the following script: Good morning, I am [your name] and I came to this village to learn more about group today. Ask whether anyone would like to say a prayer, if appropriate, and continue: We would like to do a group activity with you. This activity will take about 30 minutes. But before we get started, I'll go around the group and will ask you some information about yourself.

Go around the group and fill in the notation sheet - all columns except for the two last columns. Use the Club Game Matching Number Table to select the column that matches the number of club members present and complete the 'Match Number' - second column.

These numbers have been drawn randomly such that the 'Number assigned for the game' is not the same as 'Match number'. While this information is not secret, keep the conversation with each member at a quiet volume. Keep track of spouses within the group as per notation sheet. Continue with the script: In this activity you will each receive 400 Kwacha in this white envelop (Hold up a white envelop). Once you receive the 400 Kwacha, we will ask you to make an important decision. You will each divide up the 400 Kwacha in two parts: one part, you will put in your pocket. This part will be yours to keep and you and your family can decide what to do with it. The other part, you will put back into the envelope. You will then place the envelope back onto the table (point to the table). Once we have all made our decision, I will open these envelopes and tell you the total amount that is in the envelopes. I will then multiply this amount by 2, and place back double onto the table. So if the total amount is 500 Kwacha, I will add 500 Kwacha and place a total of 1000 Kwacha on the table. Then, you - as a group - will have to decide what to do with this money. You can decide to spend it on something for the group, or return it to the members. That decision is up to you - as a group - together.

Emphasize the following. The decision you make will be a secret decision. This is your decision and yours only. So I will ask you to go to different corners of the square and divide the money you have in secret, without anyone seeing you. You can decide to put as much or as little as you want into the envelop, so it can be 0 or 400 KW. There is no right or wrong decision. It is just a personal decision. I will also play. (Hold up your own envelop). I will come around the square and record your decision. But it will be only me knowing your decision; I will not share this information with anyone in the village. So your decision is secret. No-one else will know what you decided.

Ask whether there are any question. If not, proceed and hand out the envelopes to everyone. Continue the script: Before you make a decision, I would like you to discuss for 5 minutes with the group what you would like to do with the group money, once you receive it. Allow the group members to discuss in your absence for 5 minutes.

Return to the group and tell the members to disperse and make their decision. After a few minutes, go around and speak to each member. It is very important that no-one else can hear you, so go further from the others if need be. Ask the individual how much they kept to themselves and note down their contribution to the pot on the next page. Then ask them whether they happen to know their match and how much acreage the match has. Note down this stated acreage on the next page. Do not pressurize people to make a decision quickly. Give them sufficient time. When everyone is done, ask them to place their envelope on the table. Mix the envelopes carefully. Then open the envelopes, and take out the funds. Do this quickly and try not to show too much how much is in each envelop. Count the total and announce the total. Then match the total and place the full amount on the table.

Ask: whom should I give this to? [Write down that person's ID]

Ask: So what does your group plan to do with this money? [Write down the answer on the next page]

Notes: Sometimes group members might ask what they can do with the money they have: emphasize that this is up to them. They should treat this money as regular normal income. Sometimes group members might want to know the exact amount they will get before they can discuss what to do. Tell them that you don't know this either, this will depend on what each person will put in, and they should try to discuss nevertheless.

Number assigned for the game	Match number	Name	Present? (Yes/No)	Household ID	Age (years)	Education (years com-pleted)	Land (acre owned)	Spouse number	Reported match acreage	Contribute
1										
2										
3										
4										
5										
6										
7										
8										
9										
10										
11										
12										
13										
14										
15										
16										
17										
18										
19										
20										

How does the group intend to use the funds from the common pot? ______________________________

C.1.2 2015 Game Instructions

Discussion Treatment

Village Number: |____|____|____|
Decision Type: |2 = Group Decides|
Pre-Game Conversation Type: |____|

GROUP GAME - INSTRUCTIONS

1 Before the Meeting Starts

- Write down the village number code in the space at the top of each sheet. Consult the randomization list and make sure you are using the correct document for the "Decision Type" (1 = leader decides, 2 = group decides). The "Pre-Game Conversation Type" will be either 1 = Control, 2 = Ability, or 3 = Values. Write down the "Pre-Game Conversation Type" at the top of every sheet. Only follow the instructions for the pre-game conversation relevant for your particular case according to the randomization list. As an aid, go through the remaining pages of this document and circle the sections you will read based on the randomization codes. Double check to make sure you are using the correct document and instructions according to the randomization list.
- Place 500 KW in 20 envelopes in notes of 50 KW, meaning 500 K per envelope. There should be at least one envelope per club member.
- If there is a CDI club in your village:
  - Consult the club listing for your village and write down the names, leadership roles and gender of each of the club members on the form titled "Game Data" attached to this document. Write down the HH ID of the households that were included in the survey in baseline.
  - First arrange to meet the CDI club leaders (chairperson, secretary, lead farmer, and treasurer) in one central village location, secluded from the rest of the village as to avoid bystanders. Arrange to have the rest of the CDI club members arrive 45 minutes later. If the entire club arrives at the same time, then take the leaders aside first to fill out the leader questionnaire and describe the activity as mentioned in section 2
- If there is NOT a CDI club in your village:
  - Arrange to meet all of the individuals in the sample in a village and write down their names, gender, and household IDs on the form titled "Game Data" attached to this document. Once everyone is present, read the following prompt:

    > We would like to invite you to participate in an activity where you will have the opportunity to provide a useful good to your households. In order for this activity to work, we would like for you to imagine that you are members of a farmers group. You can imagine that your group gets together twice a month or so to discuss various farming techniques and items of group interest using an agenda created by the group chairperson. You can also imagine that your group has a treasurer who keeps group contributions in a common fund. The group sometimes uses the funds to provide various services or items of value to club members. Each club is unique and can make different decisions regarding how to use the funds. Each club member can choose how much to contribute to the club's well-being. In the following activity you will be making hypothetical decisions associated with how the group funds will be used. You will have actual funds available to you when thinking of the decision at hand, so your decision can be acted upon if the group desires to.

  - Ask if there are any questions. If necessary, state that this is only a hypothetical exercise and that we will provide the group with funds, do not specify how at this time, to use in deciding how to spend money as a group. After addressing any questions, ask the group to choose one person to act as a temporary chairperson and one person to act as a temporary treasurer. Once these individuals are identified, specify who is the chairperson and who is the treasurer on the form titled "Game Data" in the relevant column and proceed by telling these individuals (temporary chair person and treasurer) that you have specific instructions just for then. Tell the remaining club members that you will spend

1

15 minutes or so explaining instructions to the chosen leaders and that you appreciate their patience very much as they wait. Take the leaders aside and proceed to section 2.

2 Once the Leaders are present

- Skip the sections of the exercise that are only relevant for CDI clubs only (e.g. how many group activities do you attend, etc.). As an aid, these bullets are labeled **[CDI CLUBS ONLY]**
- **[CDI CLUBS ONLY]**: Ask the leaders for their names and note whether they are present or not in the form titled "Game Data." Indicate what kind of leader they are in the "Leader" Column next to the name column (Chairperson - CP; Secretary - S; Lead Farmer - LF; Treasurer - T). Ask questions G1 to G5 on the "Game Data" form and document responses on the form.
- **[CDI CLUBS ONLY]**: (20 minutes) Say "Before I explain the nature of our activities today, I'd like to get some more information about your club. This should take about twenty minutes." Find the document titled **"Group Leaders"** attached to this document. Follow the instructions and proceed to collect relevant information.
- Once documentation is complete, read the following script:

  Good day, I am [your name] and I came to this village to learn more about the group today. I wanted to talk to you before talking to the group as a whole in order to describe some of the activities we'll be doing together today. Shortly, we will distribute some funds to each of the group members and you will all try to decide how much of these funds to give to the common funds that belong to the group. We will double whatever amount the group gives for the use of the funds that you decide on. **Before asking the group to contribute, we will ask the entire group to participate in discussions that will help describe some of the workings of the group. We will also ask the group to decide on how the funds will be used through a group discussion.** I understand that your group may make decisions in a different manner than through group discussion. If it does, then I'd like to invite you to think of this as an experiment of how decisions might be made by groups in a different way. This is what we are studying by conducting this activity, and the research group looks forward to sharing the results of this study in the future.

  During the group discussions I will ask each group member to offer their opinion on a question that I will pose to them. After each person has spoken, I will ask you to lead the group to arrive to a consensus with respect to the topic of conversation. I will share the topics of conversation once everyone is present. As you try to lead the group to a consensus regarding the decision that the group can make together, please remember that everyone's opinion should be valued equally. If disagreements arise, you can try your best to help the group find a way to overcome these disagreements, but you should try not to tell the group what to do. This is certainly not an easy task, but I only ask that you try your best to facilitate the group decision in this manner. Do you know which of you would take the lead in this manner? [allow the leaders to respond and note who would lead the discussion... this should be the chairperson] Do you have any questions for me?

- Who is leading the discussion (Name/"Game Data" ID): ______________________________

3 Once everyone is present

- Once all members are present, ask every individual to introduce themselves to the group by name. Note down who is present and who is not present on the form at the back of this document. **A minimum of 6 members should be present to play the game.**

- Read the following script

  Good day, I am [your name] and I came to this village to learn more about the group today. Before we start, would anyone like to say a prayer?

- After the prayer, say the following.

  Thank you. We would like to do a group activity with you. This activity will take about 60 minutes, but before we begin I would like to go around the group and ask you some information about yourself.

- Go around the group and fill in the "Game Data" form questions G10 through G13 for all members - all shaded columns in the middle of the table. While this information is not secret, keep the conversation with each member at a quiet volume. Keep track of spouses within the group as per question G9 on the "Game Data" form.

- At this time, you may also randomly select "Match numbers" only for individuals who are present during the game as indicated by G6. This is a task done by enumerators without discussing with game participants.

- Read the following script

  I will ask the group to participate in two different activities. In the first activity, we will discuss and agree upon the 5 most important abilities that would be good for group members to have when trying to cooperate as a group. To help you think of this list, we thought we'd describe some of the things that we've seen farmer clubs do. Clubs can manage demonstration plots in villages in order to learn about new farming techniques, have fundraisers to help group members in need, use club funds to finance a village savings group, help each other with high labor tasks on each others plots, bargain for higher prices with buyers as a group, and many other things. We are interested in hearing your thoughts on the 5 most important abilities that a club would need to have among its members (not every person has to possess all of the abilities) to successfully carry out group activities. I will first call on each of you to share your thought on ONE such important ability. After everyone has spoken, the club leaders will help you chose the five most important abilities from the list that you have created.

- Tear a sheet of paper in equal pieces according to the number of people present. Write down numbers 1, 2, 3... on each sheet so that you have one number for each participant PRESENT in the discussion. For example, if there are 12 individuals present, tear a sheet of paper into 12 equal parts and write numbers 1, 2, 3... 10, 11, 12 on each of these 12 pieces. You may need to skip numbers associated with individuals who are not present as per their identifier in the "Game Data" Form. Put all of the pieces in a hat, bowl, cup, or other container. Pull a number out of the container and refer to the form titled "Game Data" to find the name of the individual associated with this number. Leave the piece of paper with this number outside of the container. Ask this person with all other club members present "What are a few (no more than 3) abilities you think would lead to group success?" After the person lists ONE ability, record their response on the sheet titled "Randomly-sorted Ability Response." Repeat the activity (draw a new number) until everyone has spoken once. Then, read the following script:

  These are all excellent ideas! I would now like to ask the group leaders to help you take 5 minutes to choose the 5 most important abilities out of the abilities you've already chosen. Everyone is free to discuss their thoughts and all opinions should be equally considered. Please be considerate of others and do not take too much time to share your thoughts.

- Start a timer for 5 minutes. Once the timer says that there is only one minute left, tell the group that they will have to decide on their list in the next minute. If the group is able to come up with a list of 5 qualities, please note their decisions in the form at the back of this document. If they are unable to come to a decision in this time, give them 2 more minutes to discuss their list and take note of their decisions in the same form. If after the group is still unable to make a decision on the list, read the following:

  It's very useful to hear your thoughts on qualities that are important and that lead to cooperation in these groups. Even though the time was short to come to agreement on the 5 most important qualities, hopefully the discussion itself has been useful to you as you think about how your group can improve in the future.

- **If Pre-Game Conversation = 1, move to section 4.** Otherwise, read the following according to the Pre-Game Conversation Type:

  Pre-Game Conversation 2 - ABILITY Now that you have a list of the 5 most important abilities for group discussion [List the 5 abilities], turn to the person you are sitting next to (small groups no larger than 3 people) and decide who among you is particularly strong in each of these abilities. If possible, think of examples of how each person's abilities can be used to the benefit of the group. This conversation is important to the activity, so I appreciate your cooperation!

  Pre-Game Conversation 3 - VALUES Now that you have a list of the 5 most important abilities for group discussion [List the 5 abilities], turn to the person you are sitting next to (small groups no larger than 3 people) and share a story of how your group managed to come to an agreement after an initial moment of disagreement between group members. Did these abilities help lead to agreement or were other factors at play? If your group has not yet had disagreement, then share how you might overcome disagreement if it were to arise. This conversation is important to the activity, so I appreciate your cooperation!

- Spend 2-3 minutes having these small-group discussions. The idea is for everyone to have a brief conversation according to the prompt, the content of these conversations should not be recorded and need not be monitored by the enumerator.

4 Choosing and Contributing to Public Goods

- Read the following script

  In the following activity, you will each receive 500 Kwacha in this envelope (hold up an envelope). Once you receive the 500 Kwacha, we will ask you to make an important decision. You will each divide up the 500 Kwacha in two parts: one part, you will put in your pocket. This part will be yours to keep and you and your family can decide what to do with it. The other part, you will put back into the envelope. You will then place the envelope back onto the table (point to the table). Once we have all made our decision, I will open these envelopes and tell you the total amount that is in the envelopes. I will then multiply this amount by 2, and place back double onto the table. So if the total amount is 500 Kwacha, I will add 500 Kwacha and place a total of 1000 Kwacha on the table. **You will all decide together what the group will do with this total amount. You will make this decision before you decide how much to put in the envelope.** Do you have any questions?

  In the same manner as before, I would like you to decide what the best use of the funds will be. I will first call on each of you to share your thought on one way in which the funds can be used. After everyone has spoken, the club leaders will help you discuss the options that have been presented and come to a decision on how the funds will be used. Your group is free to use the funds in any way you choose.

- Return the pieces of paper with the numbers on them to the container. Repeat the same activity as earlier but with a different question. Specifically, take a number out of the container (and leave it out of the container) and refer to the "Game Data" form to find the name of the individual associated with the number. Ask this individual "Please briefly describe your opinion on how the money should be spent by the group." Record responses in the form titled "Randomly-Sorted Decision Response." After the person finishes their thought, repeat the activity (draw a new number), until everyone has spoken once. Then, read the following script:

  Again, these are excellent thoughts. I would now like to ask you to spend 5 minutes to discuss the various options with the help of your group leaders. By the end of five minutes you should have a decision on how to spend the group's money. After this, each of you will decide how much of the 500 Kwacha to leave in the envelope and how much to put in your pockets.

- Start a timer for 5 minutes and remain listening to the group's conversation, but do not say anything! Once the timer says that there are only 2 minutes left, tell the group that they will have to decide on their list in the next two minutes. If the group has completed their decision, please note their decision in the form titled "Decision for Use of Common Funds" at the back of this document. Also note how long it took (in minutes) for the group to make their decision. If they are unable to come to a decision in this time, give them 2 more minutes to discuss their list and take note of their decisions in the same form. Note why it took long for the group to come up with their decision. In either case, read the following:

  > It's very useful to hear your thoughts on how to use the funds. You are free to think further about how to use the funds after you receive the common pot at the end of this activity if you need more time.

5 Return to Group

- Read the following prompt:

  > You have decided to use the funds for [read the decision that was arrived at and that you documented in question 2]. Now that we know how the funds will be used I would like to ask you to make your decisions on how much to put in the envelope. [Emphasize the following] **I want you to know that the decision you make will be a secret decision. This is your decision and yours only. So when it is time to decide how much money to put in the envelope, I will ask you to go to different corners of the square and divide the money you have in secret, without anyone seeing you.** You can decide to put as much or as little as you want into the envelope, so it can be 0 or 500 KW or anything in between. I will come around the circle and record your decision. But it will be only me knowing your decision; I will not share this information with anyone in the village. Your decision is secret. No-one else will know what you decided.

- Ask whether there are any questions. If not, proceed and hand out the envelopes to everyone. Tell the members to disperse and make their decision. Make sure they are not in earshot of one another.
- After a few minutes, go around and speak to each member. It is very important that no-one else can hear you, so go further from the others if need be. Ask the individual questions G14-G18 on the "Game Data" form and fill in G9-G12 if not yet filled in. Ask them whether they happen to know their match and how much acreage the match has. Note down this stated acreage on the next page. Ask the individuals how much they kept to themselves and note down their contribution to the pot on "Game Data" form. After they share their contribution amount, ask them for the envelope and move on to the next person. Once information has been collected for the entire group, come back to the area where the group is gathered.
- Mix the envelopes carefully. Then open the envelopes and take out the funds. Do this quickly and try not to show too much how much is in each envelope. Count the total in a public fashion and announce the total (e.g. count outloud for each 50 KW bill). Then match the total and place the full amount on a table.
- If the treasurer of the group is present, tell the group that you will hand the funds to the treasurer. If the treasurer is not present, ask "Who shall I give this amount to?"
- Write down that person's ID number as listed on the "Game Data" Form. ____________

THE FOLLOWING INSTRUCTIONS (IN THIS BOX) ARE ONLY FOR THE CASE WHERE THE GROUP PLAYING THE GAME IS <u>NOT</u> A CDI CLUB

- At the end of the activity, you may read the following:

  > Since those of you who have participated in an activity may not actually be members of a farmer club, we would like to give you the following option. Please decide whether you would like to use the funds in the way that was decided during the activity, or whether you would like for us to return the funds in equal shares to each of you.

Village Number: |____|____|____|
Decision Type: |2 = Group Decides|
Pre-Game Conversation Type: |____|

- Allow the group some time to decide whether they would like to receive the funds as a group or whether they would like to receive the funds in equal shares. I they would like to receive the funds in equal shares, divide the funds in as equal shares as possible. Otherwise, if the group decides to use the funds in the matter they decided originally, hand the funds to the treasurer. If there are funds left over that can not be be divided equally, mark this amount (it should be less than 50KW $\times$ The number of people playing the game) separately. Take note of the decision and the remaining money on the following lines.

- **Decision**. Circle one of the following: Group Use of Funds / Divide in Equal Shares

- **Remaining Amount**. ____________________

6 Notes

- Sometimes group members or leaders might ask what they can do with the money they have: emphasize that this is up to them. They should treat this money as regular normal income.
- Sometimes group members might want to know the exact amount they will get before they can discuss what to do. Tell them that you don't know this either, this will depend on what each person will put in, and they should try to discuss nevertheless.
- Sometimes group members will say that the decision-making process is not the same one they employ in their group meetings. Tell them that you understand this and apologize if it creates difficulties but that it is part of an experiment to study ways in which groups can make decisions together. Hopefully the group can discuss the outcomes of their experience with each other after the activity and compare it with how they usually make decisions.

Leader Treatment

GROUP GAME - INSTRUCTIONS

1 Before the Meeting Starts

- Write down the village number code in the space at the top of each sheet. Consult the randomization list and make sure you are using the correct document for the "Decision Type" (1 = leader decides, 2 = group decides). The "Pre-Game Conversation Type" will be either 1 = Control, 2 = Ability, or 3 = Values. Write down the "Pre-Game Conversation Type" at the top of every sheet. Only follow the instructions for the pre-game conversation relevant for your particular case according to the randomization list. As an aid, go through the remaining pages of this document and circle the sections you will read based on the randomization codes. Double check to make sure you are using the correct document and instructions according to the randomization list.
- Place 500 KW in 20 envelopes in notes of 50 KW, meaning 500 K per envelope. There should be at least one envelope per club member.
- If there is a CDI club in your village:
  - Consult the club listing for your village and write down the names, leadership roles and gender of each of the club members on the form titled "Game Data" attached to this document. Write down the HH ID of the households that were included in the survey in baseline.
  - First arrange to meet the CDI club leaders (chairperson, secretary, lead farmer, and treasurer) in one central village location, secluded from the rest of the village as to avoid bystanders. Arrange to have the rest of the CDI club members arrive 45 minutes later. If the entire club arrives at the same time, then take the leaders aside first to fill out the leader questionnaire and describe the activity as mentioned in section 2
- If there is NOT a CDI club in your village:
  - Arrange to meet all of the individuals in the sample in a village and write down their names, gender, and household IDs on the form titled "Game Data" attached to this document. Once everyone is present, read the following prompt:

    > We would like to invite you to participate in an activity where you will have the opportunity to provide a useful good to your households. In order for this activity to work, we would like for you to imagine that you are members of a farmers group. You can imagine that your group gets together twice a month or so to discuss various farming techniques and items of group interest using an agenda created by the group chairperson. You can also imagine that your group has a treasurer who keeps group contributions in a common fund. The group sometimes uses the funds to provide various services or items of value to club members. Each club is unique and can make different decisions regarding how to use the funds. Each club member can choose how much to contribute to the club's well-being. In the following activity you will be making hypothetical decisions associated with how the group funds will be used. You will have actual funds available to you when thinking of the decision at hand, so your decision can be acted upon if the group desires to.

  - Ask if there are any questions. If necessary, state that this is only a hypothetical exercise and that we will provide the group with funds, do not specify how at this time, to use in deciding how to spend money as a group. After addressing any questions, ask the group to choose one person to act as a temporary chairperson and one person to act as a temporary treasurer. Once these individuals are identified, specify who is the chairperson and who is the treasurer on the form titled "Game Data" in the relevant column and proceed by telling these individuals (temporary chair person and treasurer) that you have specific instructions just for then. Tell the remaining club members that you will spend

15 minutes or so explaining instructions to the chosen leaders and that you appreciate their patience very much as they wait. Take the leaders aside and proceed to section 2.

2 Once the Leaders are present

- Skip the sections of the exercise that are only relevant for CDI clubs only (e.g. how many group activities do you attend, etc.). As an aid, these bullets are labeled **[CDI CLUBS ONLY]**
- **[CDI CLUBS ONLY]**: Ask the leaders for their names and note whether they are present or not in the form titled "Game Data." Indicate what kind of leader they are in the "Leader" Column next to the name column (Chairperson - CP; Secretary - S; Lead Farmer - LF; Treasurer - T). Ask questions G1 to G5 on the "Game Data" form and document responses on the form.
- Once documentation is complete, read the following script:

  > Good day, I am [your name] and I came to this village to learn more about the group today. I wanted to talk to you before talking to the group as a whole in order to describe some of the activities we'll be doing together today. Shortly, we will distribute some funds to each of the group members and you will all try to decide how much of these funds to give to the common funds that belong to the group. **Before asking the group to contribute, we will ask the leaders of the group, you, to decide how the funds will be used.** We will double whatever amount the group gives for the use of the funds that you decide on. I understand that your group may make decisions in a different manner than by having the leaders determine the outcome. If it does, then I'd like to invite you to think of this as an experiment of how decisions might be made by groups in a different way. This is what we are studying by conducting this activity, and the research group looks forward to sharing the results of this study in the future.

- **[CDI CLUBS ONLY]**: (20 minutes) Say "First, I'd like to get some more information about your club. This should take about twenty minutes." Find the document titled **"Group Leaders"** attached to this document. Follow the instructions and proceed to collect relevant information.
- The following script initiates the first decision that the leaders will have to make. Read the following:

  > Before doing this activity, however, we would like you to spend 5 minutes listing 5 important attributes that would be good for group members and groups to have when trying to cooperate. To help you think of this list, we thought we'd describe some of the things that we've seen farmer clubs do. Clubs can manage demonstration plots in villages in order to learn about new farming techniques, have fundraisers to help group members in need, use club funds to finance a village savings group, help each other with high labor tasks on each others plots, bargain for higher prices with buyers as a group, and many other things. We are interested in hearing your thoughts on the top 5 most important attributes that a group and group members would need to have in order for the club to be successful in some of these activities. Again, you have five minutes to come up with this list; please write down your decision on this sheet of paper.

- Hand the leaders the attached sheet titled "5 Attributes of Successful Groups" and ask them to write their decisions on this sheet. Mention that this sheet will be handed back to the enumerators.
- Start a timer and allow the leaders 5 minutes to come up with this kind of list. Make sure that they decide on 5 (and only 5) of the most important abilities. It is important that they not mention more than 5, but that if they come up with more than 5 abilities, they decide which are the top 5 most important combined abilities for group success.
- If the leaders have not completed the activity after 5 minutes, ask "Do you need 1 more minute to complete the activity?" If yes, grant them one more minute to fill as many slots on the sheet as they can. After the extra minute is up, ask them to hand in the sheet even if it is incomplete.

- If the **Pre-Game Conversation = 1** then proceed to section 4. If the **Pre-Game Conversation = 2 OR 3**, proceed to section 3 by saying "Thank you for your effort in coming up with this list. Let us return to the group where we will share this list with the rest of the group members."

3 Everyone is present

- NOTE: IF **PRE-GAME CONVERSATION = 1**, then you should skip this section entirely and go straight to section 4. Do not gather the group together until AFTER section 4.
- Now that the first activity with the club leaders is complete, invite everyone to gather together and sit in a circle.
- Once all members are present, ask every individual to introduce themselves to the group by name. Note down who is present and who is not present on question G6 on form titled "Game Data" attached to this. Make sure the sex (G8) of each group member is correctly recorded. If an individual is being represented by a spouse or other family member during the activity, please note this in question G9 in the form titled "Game Data."
- **A minimum of 6 members should be present to play the game.** If this is the case, read the following script:

  > Good day, I am [your name] and I came to this village to learn more about the group today. Before we start, would anyone like to say a prayer?

- After the prayer is said, say the following:

  > Thank you. We would like to do a group activity with you. This activity will take about 45 minutes, but before we begin I would like go around the group and ask you some information about yourself.

- Go around the group and fill in the "Game Data" form questions G10 through G13 for all members - all shaded columns in the middle of the table. While this information is not secret, keep the conversation with each member at a quiet volume. Keep track of spouses within the group as per question G9 on the "Game Data" form.
- At this time, you may also randomly select "Match numbers" only for individuals who are present during the game as indicated by G6. This is a task done by enumerators without discussing with game participants.
- Read the following according to the Pre-Game Conversation Type:

  > I would now like to explain a few instructions on the side to the leaders you identified earlier. While the rest of you wait, I would like you to do the following activity:

  Pre-Game Conversation 2 - ABILITY Your group leaders have identified the following 5 abilities as important abilities that lead to success in group activities [List the 5 abilities the leaders came up with]. Turn to the person you are sitting next to (small groups no larger than 3 people) and decide who among you is particularly strong in each of these abilities. If possible, think of examples of how each person's abilities can be used to the benefit of the group. This conversation is important to the activity, so I appreciate your cooperation!

  Pre-Game Conversation 3 - VALUES Your group leaders have identified the following 5 abilities as important abilities that lead to success in group activities [List the 5 abilities the leaders came up with]. Turn to the person you are sitting next to (small groups no larger than 3 people) and share a story of how your group managed to come to an agreement after an initial moment of disagreement between group members. Did these abilities help lead to agreement or were other factors at play? If your group has not yet had disagreement, then share how you might overcome disagreement if it were to arise. This conversation is important to the activity, so I appreciate your cooperation!

4 Talking to Leaders

- Take the leaders identified earlier aside and read the following script:

  The activity that follows will help us understand how different decision-making processes can lead to different outcomes in group cooperation. Earlier, I told the group that you will make the decisions on how to use the funds. I understand that your group may make decisions in a different manner than the one I described. If it does, then I'd like to invite you to think of this as an experiment of how decisions might be made by groups in a different way. This is what we are studying by conducting this activity, and the research group looks forward to sharing the results of this study in the future. In your particular case, I would like you to follow the following procedure for making a decision.

  Before the group members decides how much to contribute, I would like you to decide what the best use of the funds will be. Please take the next 5 minutes to decide what your group will use the funds to do. Please keep this conversation among yourselves, do not talk to other group members when making this decision. When I return, I would like you to tell me your decision. Then, we will reunite with the rest of the group and you will tell them your decision. After that, the group members (yourselves included) will decide how much to put in the envelope. Do you have any questions?

- Allow 5 minutes for the leaders to make their decisions. Start a timer (perhaps on your phone) for five minutes. *[These two sentences only for **Pre-game Conversation = 2 OR 3**: While you wait, feel free to listen in on the conversations the rest of the group members are having in pairs or groups of three. If groups are not talking, approach them and ask them if they have discussed the pre-game conversation at length or whether they would like to hear the instructions again.]* When the leaders are ready, note the decision that is made on the form at the end of this document titled "Decision for Use of Common Funds." Note how many minutes it took for the leaders to come up with this decision. If the leaders spend more than 5 minutes, ask them why the decision is taking longer than 5 minutes and note the reason down in the available slot in the same form. If needed, urge them to finalize the decision since the group is waiting for a response. Remember, do not allow the leaders to discuss this decision with the rest of the group.

5 Return to Group

If Pre-Game Conversation = 1, then this is the first time you are with all of the club members. Do the tasks outlined in this box. Otherwise, skip this box.

- Now that the first activity with the club leaders is complete, invite everyone to gather together and sit in a circle.
- Once all members are present, ask every individual to introduce themselves to the group by name. Note down who is present and who is not present on question G6 on form titled "Game Data" attached to this. Make sure the sex (G8) of each group member is correctly recorded. If an individual is being represented by a spouse or other family member during the activity, please note this in question G9 in the form titled "Game Data."
- **A minimum of 6 members should be present to play the game.** If this is the case, read the following script:

  Good day, I am [your name] and I came to this village to learn more about the group today. Before we start, would anyone like to say a prayer?

- After the prayer is said, say the following:

Village Number: |____|____|____|
Decision Type: |1 = Leader Decides|
Pre-Game Conversation Type: |____|

Thank you. We would like to do a group activity with you. This activity will take about 45 minutes, but before we begin I would like to go around the group and ask you some information about yourself.

- Go around the group and fill in the "Game Data" form questions G10 through G13 for all members - all shaded columns in the middle of the table. While this information is not secret, keep the conversation with each member at a quiet volume. Keep track of spouses within the group as per question G9 on the "Game Data" form.
- At this time, you may also randomly select "Match numbers" only for individuals who are present during the game as indicated by G6. This is a task done by enumerators without discussing with game participants.

- Read the following script

  In the following activity, you will each receive 500 Kwacha in this envelope (hold up an envelope). Once you receive the 500 Kwacha, we will ask you to make an important decision. You will each divide up the 500 Kwacha in two parts: one part, you will put in your pocket. This part will be yours to keep and you and your family can decide what to do with it. The other part, you will put back into the envelope. You will then place the envelope back onto the table (point to the table). Once we have all made our decision, I will open these envelopes and tell you the total amount that is in the envelopes. I will then multiply this amount by 2, and place back double onto the table. So if the total amount is 500 Kwacha, I will add 500 Kwacha and place a total of 1000 Kwacha on the table. **The leaders you identified earlier will decide what to do with this total amount and inform you of their decision before you decide how much to put in the envelope.** Do you have any questions?

- After any questions are addressed, read the following prompt:

  The leaders of your group have decided to use the funds in the following manner [read the decision that was arrived at and that you documented in the "Decision for Use of Common Funds" form]. Now that we know how the funds will be used I would like to ask you to make your decisions on how much to put in the envelope. [Emphasize the following] **I want you to know that the decision you make will be a secret decision. This is your decision and yours only. So when it is time to decide how much money to put in the envelope, I will ask you to go to different corners of the square and divide the money you have in secret, without anyone seeing you.** You can decide to put as much or as little as you want into the envelope, so it can be 0 or 500 KW or anything in between. I will come around the circle and record your decision. But it will be only me knowing your decision; I will not share this information with anyone in the village. Your decision is secret. No-one else will know what you decided.

- Ask whether there are any questions. If not, proceed and hand out the envelopes to everyone. Tell the members to disperse and make their decision. Make sure they are not in earshot of one another.
- After a few minutes, go around and speak to each member. It is very important that no-one else can hear you, so go further from the others if need be. Ask the individual questions G14-G18 on the "Game Data" form and fill in G9-G12 if not yet filled in. Ask them whether they happen to know their match and how much acreage the match has. Note down this stated acreage on the next page. Ask the individuals how much they kept to themselves and note down their contribution to the pot on the "Game Data" form. After they share their contribution amount, ask them for the envelope and move on to the next person. Once information has been collected for the entire group, come back to the area where the group is gathered.
- Mix the envelopes carefully. Then open the envelopes and take out the funds. Do this quickly and try not

to show too much how much is in each envelope. Count the total in a public fashion and announce the total (e.g. count outloud for each 50 KW bill). Then match the total and place the full amount on a table.

- If the treasurer of the group is present, tell the group that you will hand the funds to the treasurer. If the treasurer is not present, ask "Who shall I give this amount to?"
- Write down that person's ID number as listed on the "Game Data" Form. ____________

THE FOLLOWING INSTRUCTIONS (IN THIS BOX) ARE ONLY FOR THE CASE WHERE THE GROUP PLAYING THE GAME IS NOT A CDI CLUB

- At the end of the activity, you may read the following:

  > Since those of you who have participated in an activity may not actually be members of a farmer club, we would like to give you the following option. Please decide whether you would like to use the funds in the way that was decided during the activity, or whether you would like for us to return the funds in equal shares to each of you.

- Allow the group some time to decide whether they would like to receive the funds as a group or whether they would like to receive the funds in equal shares. I they would like to receive the funds in equal shares, divide the funds in as equal shares as possible. Otherwise, if the group decides to use the funds in the matter they decided originally, hand the funds to the treasurer. If there are funds left over that can not be be divided equally, mark this amount (it should be less than 50KW × The number of people playing the game) separately. Take note of the decision and the remaining money on the following lines.

- **Decision**. Circle one of the following: Group Use of Funds / Divide in Equal Shares

- **Remaining Amount**. ________________________________

6 Notes

- Sometimes group members or leaders might ask what they can do with the money they have: emphasize that this is up to them. They should treat this money as regular normal income.
- Sometimes group members might want to know the exact amount they will get before they can discuss what to do. Tell them that you don't know this either, this will depend on what each person will put in, and they should try to discuss nevertheless.
- Sometimes group members will say that the decision-making process is not the same one they employ in their group meetings. Tell them that you understand this and apologize if it creates difficulties but that it is part of an experiment to study ways in which groups can make decisions together. Hopefully the group can discuss the outcomes of their experience with each other after the activity and compare it with how they usually make decisions.

GAME DATA

Village: |___|___|___|
Decision Type: ______________________
Pre-Game Conversation Type: __________

ENUMERATOR		ENUMERATOR GETS INFORMATION DURING CONVERSATION WITH GROUP LEADERS							ENUMERATOR NOTES RESPONSES DURING GROUP INTRODUCTIONS				ENUMERATOR GETS INFORMATION AFTER INTRODUCTIONS				ENUMERATOR GETS INFORMATION MEMBERS AFTER CONTRIBUTION IS MADE						
Number assigned for the game	Match number	Name	G1 Leader Role? (CP, S, LF, T)	[LEADERS ONLY] G2 were you a leader last year?	G3.	G3a. If G3 = "NOT IN VILLAGE", Village Name?	G4	G5	G6. Present? (Yes/No)	G7. Household ID (if in sample)	G8 Sex (M/F)	G9 Represented by Family Member (Y/N)	G10. Age (years)	G11. Education (years completed)	G12. Land (acre owned)	G13.Does your dwelling have iron sheets?	G14	G15	G16	G17	G18	Reported Match Acreage	Contribute
1																							
2																							
3																							
4																							
5																							
6																							
7																							
8																							
9																							
10																							
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20																							
21																							
22																							
23																							
24																							
25																							

[G2-G5] CDI CLUBS ONLY

G3 [ASK THE LEADERS] Are there any individuals in the group who do not live in the village? If yes, who? [MARK THE BOXES OF INDIVIDUALS WHO DO NOT LIVE IN THE VILLAGE. CODE: 0 = IN VILLAGE 1 = NOT IN VILLAGE]
G4 [ASK THE LEADERS] Are there any individuals in the group who do not attend meetings regularly? If yes, who? [MARK THE BOXES OF INDIVIDUALS WHO DO NOT ATTEND REGULARLY. CODE: 0 = REGULAR; 1 = NOT REGULAR]
G5 [ASK THE LEADERS] Are there any individuals who have joined the group in the last year? If yes, who? [MARK THE BOXES OF INDIVIDUALS WHO ARE NEW TO THE GROUP. CODE: 0 = OLD MEMBER; 1 = NEW MEMBER]
[READ THE FOLLOWING STATEMENT BEFORE ASKING THE FOLLOWING QUESTIONS]

NOTE TO ENUMERATOR: If not with a CDI club, change wording of G14, G16, and G17 to refer to the activity they just participated in.
In other words, G14 would be "The club will effectively use the group funds contributed today." G16 would be "I was able to express opinions in the meeting today" And so on.

In the next set of statements I want you to respond with one of 5 options: 1 = Strongly Agree; 2 = Somewhat Agree; 3 = Neither Agree nor Disagree; 4 = Somewhat Disagree; 5 = Strongly Disagree. Are these instructions clear?
G14. The club was very effective in its use of group funds in the last year
G15 I often take risks in important decisions affecting my household
G16 I am able to express my opinions in group meetings
G17 Others listen to my opinions and take them seriously in group meetings
G18 The leadership of this group is very effective

Match Number: Use a random number generator to match each individual with another individual who is PRESENT during the game.
[Reported Match Acreage] Ask the individual to state the acreage of the random match within the group and record the response. Code for "I don't know" = -99.
Contribute: Ask the individual to state how much they are contributing to the group. In other words, how much of the money in the envelope are you leaving in the envelope?

Constructing Decision-Making Variable

Table C1: Individual Responses to Decision-Making Process Used by Farmer Club

"How did the club make decisions in the past year?"	N	%
(1=) "The leader decides and informs the other group members"	45	17.2%
(2=) "The leader asks the group what they think and then decides"	89	34.1%
(3=) "The group members hold a discussion and decide together"	106	40.6%
(4=) "Other"	21	8.1%
Total	261	100.0%

Out of the 87 farmer clubs that played the public goods game game, only one village did not have any survey respondents participate in the organisational participation module of the household questionnaire. Each individual survey respondent listed the civic associations that the household participates in. Using the administrative records, we identified CDI clubs in each village and tagged responses by individuals who stated that a household member is also a CDI club member. In this manner we identified 437 household heads who stated household membership in a CDI club. Each of these individuals was asked how the group usually made decisions in the past year and responded either (1=) "The leader decides and informs the other group members" (2=) "The leader asks the group what they think and then decides" or (3=) "The group members hold a discussion and decide together"[1].

Table C1 shows individual responses to this question. The survey was administered roughly 1-2 months after many of the clubs had formed[2], thus many of the respondents did not provide a response to this question - only 261 out of 437 possible responses were captured - 12 villages did not have any club members provide information regarding this question and are thus omitted from the analysis. Of the 261 responses, roughly half of the respondents

[1]Survey respondents were also allowed to respond (4=) "Other."

[2]A few clubs were in existence prior to being registered as CDI clubs, though we do not have data on the year of club formation.

indicated a more centralised decision-making regime in which club leaders are responsible for collective decision making - 51.3% of respondents chose option number 1 or 2. Only 8% of the respondents chose "other," indicating that the three options sufficiently outline the set of decision-making styles employed by the majority of the clubs.

After omitting responses by individuals indicating "other" as a response to this question, we average club-level responses in our effort to impose a common decision-making rule on all club members in each farmer club. Naturally, we would like to know what the variation in responses look like when we impose such a rule. First, we note that variation in this response is also a function of the number of individuals responding to this question. Only one individual provided a response to this question in 11 of our study farmer clubs whereas multiple individuals provided responses in the remaining 63 villages. Table C2 displays the number of responses and the variation in responses according to the number of respondents. Of note is the fact that close to 40% of the clubs had zero variation in responses to this question when there were multiple responses available and a majority (60%) of clubs with at least 2 respondents had negligible variation in responses (measured by mean standard error less than 0.3). Since only response number 3 is indicative of a fully democratic decision making style adopted by the club we see that clubs adopting this method have lower mean standard error in club-level responses, as expected - 80% of these clubs had negligible variation in responses to this question.

We note that the regression results throughout the paper are not sensitive to replacing a dichotomous measure of democracy with a continuous measure as demonstrated in table C5. In fact, the dichotomous measure attenuates coefficients of interest (correlation between democratic decision making and contribution in public goods game), which is expected since a club may be labelled "democratic" when it may not in fact be such.

Our IV estimation strategy aggregates information regarding the decision-making methods used in non-CDI village clubs in much the same way as presented above by creating a variable that only aggregates information from clubs that are not recognised in our data as CDI clubs. This includes non-CDI clubs that both CDI and non-CDI households participate in at the village level (e.g. village savings and loans organisations, women's clubs, village committees and other civic associations organised by non-CDI NGOs).

For the sake of transparency, table C3 presents the full set of responses to this question for each of the 74 CDI farmer clubs for which data are available.

TABLE C2: Decision-Making By N of Respondents

Respondents by Club	Mean SE = 0			Mean SE < 0.3			Mean SE < 0.5			Total		
	T	L	D	T	L	D	T	L	D	T	L	D
1 Response	11	4	7	11	4	7	11	4	7	11	4	7
2 Respondents	9	4	5	9	4	5	12	4	8	16	8	8
3 Respondents	7	3	4	8	3	5	9	4	5	13	7	6
4 Respondents	4	2	2	10	3	7	15	5	10	15	5	10
5 Respondents	4	3	1	9	4	5	16	11	5	16	11	5
6 Respondents	0	0	0	1	1	0	3	2	1	3	2	1
Sub-Total	35	16	19	48	19	29	66	30	36	74	37	37
% of Total	47%	43%	51%	65%	51%	78%	89%	81%	97%	100%	100%	100%
% of Total Excluding Clubs with 1 Response	38%	19%	31%	59%	31%	69%	87%	73%	96%	100%	100%	100%

Note: "T" indicates total, "L" indicates "Leader Driven" and "D" indicates "Democratic."

Table C3: Decision Making Responses

Club ID	Response to "How did this club usually make decisions" =1	=2	=3	N	Mean	Type	Mean SE
1	0	2	0	2	2.0	L	0.00
2	1	0	0	1	1.0	L	N/A
3	1	3	0	4	1.8	L	0.22
4	0	0	3	3	3.0	D	0.00
5	2	0	1	3	1.7	L	0.54
6	0	1	0	1	2.0	L	N/A
7	0	1	2	3	2.7	D	0.27
8	0	0	3	3	3.0	D	0.00
9	4	0	0	4	1.0	L	0.00
10	0	3	0	3	2.0	L	0.00
11	1	0	1	2	2.0	L	0.71
12	2	0	0	2	1.0	L	0.00
13	1	1	2	4	2.3	D	0.41
14	0	0	4	4	3.0	D	0.00
15	0	0	1	1	3.0	D	N/A
16	0	3	2	5	2.4	D	0.22
17	1	0	0	1	1.0	L	N/A
18	0	3	1	4	2.3	D	0.22
19	1	2	3	6	2.3	D	0.30
20	1	2	2	5	2.2	L	0.33
21	1	2	2	5	2.2	L	0.33
22	0	0	1	1	3.0	D	N/A
23	2	0	0	2	1.0	L	0.00
24	0	3	2	5	2.4	D	0.22
25	0	1	0	1	2.0	L	N/A
26	1	2	1	4	2.0	L	0.35
27	0	3	0	3	2.0	L	0.00
28	0	4	0	4	2.0	L	0.00
29	1	0	1	2	2.0	L	0.71
30	0	2	2	4	2.5	D	0.25
31	0	5	0	5	2.0	L	0.00
32	0	5	0	5	2.0	L	0.00
33	2	0	1	3	1.7	L	0.54
34	2	2	1	5	1.8	L	0.33

Note: "L" Indicates "Leader Driven" and "D" Indicates "Democratic."

Continued on next page...

Table C3 – continued from previous page

Club ID	Response to "How did this club usually make decisions" =1	=2	=3	N	Mean	Type	Mean SE
35	1	0	2	3	2.3	D	0.54
36	0	2	2	4	2.5	D	0.25
37	2	1	2	5	2.0	L	0.40
38	1	2	2	5	2.2	L	0.33
39	3	1	2	6	1.8	L	0.37
40	2	2	1	5	1.8	L	0.33
41	1	3	2	6	2.2	L	0.28
42	2	0	1	3	1.7	L	0.54
43	0	0	4	4	3.0	D	0.00
44	0	1	4	5	2.8	D	0.18
45	0	1	3	4	2.8	D	0.22
46	0	0	2	2	3.0	D	0.00
47	1	0	3	4	2.5	D	0.43
48	0	0	2	2	3.0	D	0.00
49	0	0	2	2	3.0	D	0.00
50	0	0	2	2	3.0	D	0.00
51	0	2	2	4	2.5	D	0.25
52	0	0	3	3	3.0	D	0.00
53	0	1	1	2	2.5	D	0.35
54	0	1	1	2	2.5	D	0.35
55	0	0	5	5	3.0	D	0.00
56	0	0	1	1	3.0	D	N/A
57	1	0	1	2	2.0	L	0.71
58	0	0	1	1	3.0	D	N/A
59	0	1	1	2	2.5	D	0.35
60	0	0	2	2	3.0	D	0.00
61	2	1	1	4	1.8	L	0.41
62	1	0	3	4	2.5	D	0.43
63	0	0	1	1	3.0	D	N/A
64	1	0	1	2	2.0	L	0.71
65	0	3	2	5	2.4	D	0.22
66	1	2	2	5	2.2	L	0.33
67	1	4	0	5	1.8	L	0.18
68	0	3	0	3	2.0	L	0.00
69	0	0	3	3	3.0	D	0.00
70	0	5	0	5	2.0	L	0.00

Note: "L" Indicates "Leader Driven" and "D" Indicates "Democratic."

Continued on next page...

Table C3 – continued from previous page

	Response to "How did this club usually make decisions"						
Club ID	=1	=2	=3	N	Mean	Type	Mean SE
71	0	2	0	2	2.0	L	0.00
72	1	1	1	3	2.0	L	0.47
73	0	0	1	1	3.0	D	N/A
74	0	0	1	1	3.0	D	N/A
Total	45	89	106	240	2.3	-	0.75*

Note: "L" Indicates "Leader Driven" and "D" Indicates "Democratic."

* Standard Deviation reported as opposed to Mean Standard Error.

Appendix Tables and Figures

Table C4: Summary Statistics of Club Level Variables as Used in Analysis

	N	Mean	Sd	Median	Max
Panel A - Decision-Making Method					
Democratic (Dichotomous)	74	0.50	0.50	0.5	1.0
Heterogeneity in Responses (Mean SE)	74	0.24	0.28	0.2	1.0
Panel B - Village Characteristics:					
Log: Distance to paved road (km)	74	0.71	0.75	0.3	2.6
Log: N of HH in village	74	4.01	0.65	4.0	6.0
Log: Price of Labour During Harvest	74	6.66	0.79	6.6	8.9
No Visits by Gov. Extension (year)	74	0.27	0.45	0.0	1.0
No Visits by NGO Extension (year)	74	0.28	0.45	0.0	1.0
N organisations from village questionnaire	74	1.97	1.26	2.0	5.0
Panel C - Other Club Variables:					
N game players	74	12.88	4.89	12.5	20.0
Club Mean: Female (0-1)	74	0.49	0.18	0.5	0.9
Club Mean: Age	74	38.73	5.03	38.7	50.6
Club Mean: Years of Education	74	5.41	1.62	5.4	9.6
Log: Avg. Land Owned	74	1.37	0.49	1.4	2.5
Log: Avg. Asset Value	71	11.59	0.90	11.6	14.6
Club Sd: Female (0-1)	74	0.48	0.07	0.5	0.5
Club Sd: Age	74	12.38	2.87	12.7	18.7
Club Sd: Years of Education	74	3.14	0.83	3.2	5.0
Log: Sd. Land Owned	74	0.86	0.77	0.8	3.2
Log: Sd. Asset Value	71	11.60	1.15	11.5	15.2
Panel D - Social Interaction Variables:					
Club Mean: Percent Approachable (0-1)	71	0.00	0.14	0.0	0.2
Club Sd: Percent Approachable (0-1)	71	0.17	0.13	0.1	0.5

All variables in this table summarise variables as used in all estimation tables (other than 4.3 as part of our empirical analysis. Variables with right-skewed distributions are log-transformed due to the relatively small sample used in the analysis . “Club Mean: Percent Approachable” in Panel D is de-meaned in the analysis, hence the mean value reported above is zero.

Table C5: Effect of Continuous Decision-Making on Cooperation in Public Goods Game

	(1)	(2)	(3)	(4)	(5)
Main effects:					
Democratic (Continuous)	0.20**	0.23**	0.24**	0.38**	0.59**
	(0.10)	(0.10)	(0.11)	(0.15)	(0.20)
Network Variables	No	Yes	Yes	Yes	Yes
Club Variables	Yes	Yes	Yes	Yes	Yes
Village Variables	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.19	0.21	0.33	0.40	0.47
Observations	71	71	62	48	34

Standard errors in parentheses. Dependent variable equals the average share (0-1) of the game endowment contributed by club. Club-and-village-level controls are same as in column (4) of table 4.5 (with the exception of column (1) - the controls here are the same as in column (3) of table 4.5). The "Democratic (Continuous)" variable has been normalised such that a value equal to 1 (0) is consistent with a scenario in which all of the club members reporting on the decision-making method stated that the club utilised democratic (leader driven) decision-making. Column (3) Limits analysis to clubs in which 2 or more individuals provided information on decision-making methods employed; (4) limits analysis to 3 or more and (5) limits analysis to 4 or more (there are not enough degrees of freedom to limit analysis to the sample of 5 or more respondents).

Table C6: First Stage of 2SLS IV Regressions Associated with Table 4.6

	(1)	
Instrument:		
Non-CDI Orgs: Democratic = 1 (Continuous)	0.57***	(0.14)
Social Connectivity		
Club Mean: Percent Approachable (0-1)	-0.32	(0.33)
Club Variables:		
N game players	0.01	(0.01)
Heterogeneity in DMP Responses (Mean SE)	-0.13	(0.13)
Club Mean: Female (0-1)	0.17	(0.19)
Club Sd: Female (0-1)	-0.92**	(0.42)
Club Mean: Age	0.01	(0.01)
Club Mean: Years of Education	0.04*	(0.02)
Log: Avg. Land Owned	0.67***	(0.19)
Log: Avg. Asset Value	-0.07	(0.12)
Club Sd: Age	-0.01	(0.01)
Club Sd: Years of Education	0.03	(0.05)
Log: Sd. Land Owned	-0.26**	(0.09)
Log: Sd. Asset Value	0.04	(0.10)
Club Sd: Percent Approachable (0-1)	-0.99**	(0.44)
Village Variables:		
Log: Distance to paved road (km)	0.07	(0.05)
Log: N of HH in village	-0.06	(0.06)
Log: Price of Labour During Harvest	0.09*	(0.05)
No Visits by Gov. Extension (year)	0.20**	(0.10)
No Visits by NGO Extension (year)	-0.07	(0.11)
N organisations from village questionnaire	0.05	(0.03)
Adjusted R^2	0.62	
Observations	43	

First stage of 2sls IV regression associated with table 4.6. Standard errors in parentheses. DMP is short for "Decision-Making Process."

Table C7: 2SLS IV Regressions - Dichotomous Decision-Making

	(1)	(2)
Instrumented:		
Democratic (Dichotomous)	0.18*	0.36***
	(0.09)	(0.14)
Network Variables	Yes	Yes
Club Variables	Yes	Yes
Village Variables	Yes	Yes
R^2	0.53	0.45
Observations	43	43
H_0: Instrument is Exogenous		0.26
First Stage F-Statistic		7.30

Standard errors in parentheses. Column (2) shows results of a 2sls instrumental variable regression (Columns (1) is estimated using OLS and only includes the sample used in column (2)) in which club decision-making is instrumented by the decision-making norm in the rest of the village. The dependent variable equals the average share of the game endowment contributed by club. Null hypothesis test results report Wu-Hausman P-values. Club-and-village-level controls are the same as in column (4) of table 4.5. First stage of estimation reported in table C8.

Table C8: First Stage of 2SLS IV Regressions Associated with Table C7

	(1)	
Instrument:		
Non-CDI Orgs: Democratic = 1 (Continuous)	0.90**	(0.33)
Social Connectivity		
Club Mean: Percent Approachable (0-1)	-0.33	(0.80)
Club Variables:		
N game players	0.03	(0.02)
Heterogeneity in DMP Responses (Mean SE)	-0.40	(0.30)
Club Mean: Female (0-1)	0.42	(0.46)
Club Sd: Female (0-1)	-1.69	(1.01)
Club Mean: Age	0.03	(0.02)
Club Mean: Years of Education	0.06	(0.05)
Log: Avg. Land Owned	1.34***	(0.45)
Log: Avg. Asset Value	0.01	(0.29)
Club Sd: Age	-0.04	(0.03)
Club Sd: Years of Education	0.01	(0.11)
Log: Sd. Land Owned	-0.60**	(0.23)
Log: Sd. Asset Value	0.03	(0.23)
Club Sd: Percent Approachable (0-1)	-1.64	(1.06)
Village Variables:		
Log: Distance to paved road (km)	-0.00	(0.12)
Log: N of HH in village	-0.21	(0.14)
Log: Price of Labour During Harvest	0.24*	(0.12)
No Visits by Gov. Extension (year)	0.52**	(0.23)
No Visits by NGO Extension (year)	-0.25	(0.27)
N organisations from village questionnaire	0.03	(0.08)
Adjusted R^2	0.45	
Observations	43	

First stage of 2sls IV regression associated with table C7. Standard errors in parentheses. DMP is short for "Decision-Making Process."

Table C9: Balance Test Associated with Experiment Described in Section 4.4

	No Club						CDI Club			
	N	Mean	Sd	Leader	Dem.	P	N	Leader	Dem.	P
Average Contribution (0-1)	50	0.57	0.21	0.52	0.62	0.09*	101	0.73	0.72	0.73
Game-player characteristics										
Sex (1-M; 2-F)	50	1.53	0.21	1.52	1.53	0.87	101	1.47	1.48	0.61
Age (Years)	50	41.91	6.18	42.84	41.05	0.31	101	40.68	39.63	0.29
Land (Acres)	50	4.82	2.09	4.65	4.97	0.60	101	4.88	5.21	0.28
Education (Years)	50	3.42	1.72	3.50	3.35	0.77	101	4.20	4.10	0.82
Dwelling with Iron Sheets (1-Y; 2-N)	50	1.72	0.23	1.76	1.68	0.26	101	1.79	1.79	0.96
SD: Sex (1-M; 2-F)	50	0.47	0.07	0.46	0.48	0.33	101	0.49	0.48	0.32
SD: Age (Years)	50	13.77	3.41	14.15	13.42	0.45	101	13.02	13.04	0.97
SD: Land (Acres)	50	3.75	2.80	4.00	3.52	0.55	101	3.13	3.14	0.92
SD: Education (Years)	50	2.12	1.69	2.42	1.84	0.23	101	2.61	3.30	0.27
SD: Dwelling with Iron Sheets (1-Y; 2-N)	50	0.38	0.18	0.35	0.40	0.32	101	0.35	0.37	0.58
Relationships among game-players										
% Family Members (0-1)	49	0.00	0.17	0.01	-0.01	0.61	56	-0.01	-0.02	0.78
% Daily Conversation (0-1)	49	0.01	0.17	0.02	-0.01	0.47	56	0.01	-0.02	0.60
SD: % Family Members (0-1)	49	0.46	0.04	0.46	0.46	0.88	56	0.44	0.45	0.61
SD: % Daily Conversation (0-1)	49	0.47	0.05	0.48	0.46	0.19	56	0.46	0.46	0.74

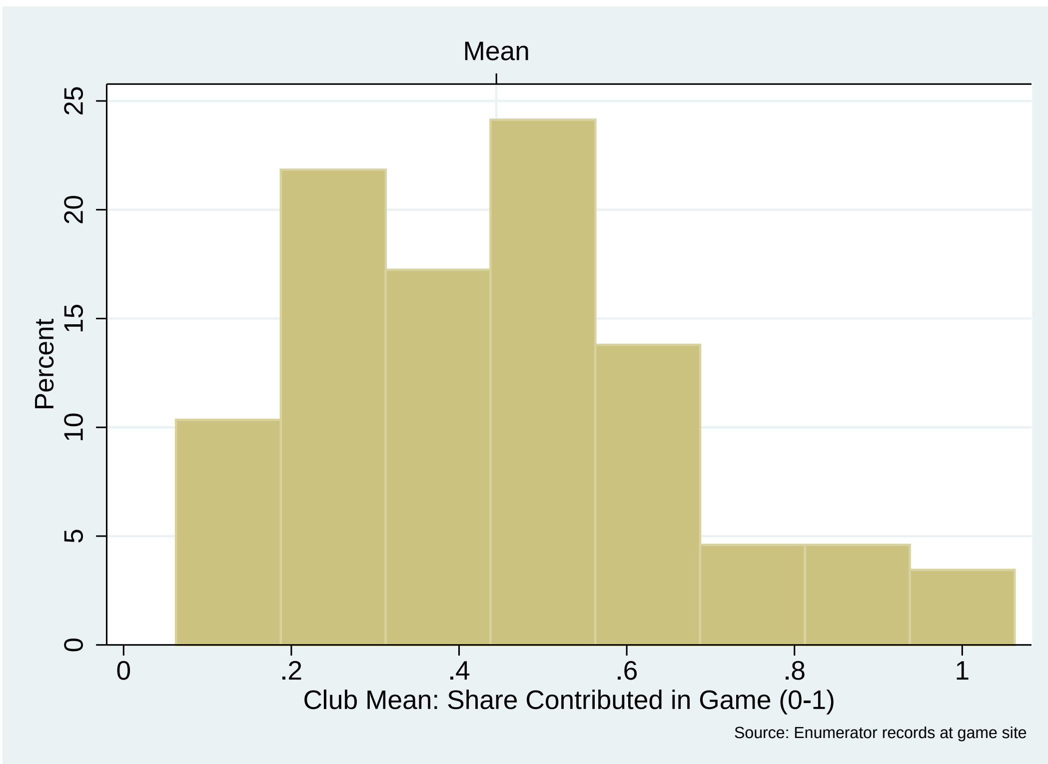

Figure C1: Histogram of Average Club Contributions to Public Goods